# ESSAYS ON CLIMATE CHANGE, AGRICULTURE AND PRODUCTION EFFICIENCY

by

Saúl Basurto Hernández

A thesis submitted to the University of Birmingham for the degree of
DOCTOR OF PHILOSOPHY

Department of Economics
Birmingham Business School
College of Social Sciences
University of Birmingham
September 2018

UNIVERSITY OF
BIRMINGHAM

**University of Birmingham Research Archive**

**e-theses repository**

This unpublished thesis/dissertation is copyright of the author and/or third parties. The intellectual property rights of the author or third parties in respect of this work are as defined by The Copyright Designs and Patents Act 1988 or as modified by any successor legislation.

Any use made of information contained in this thesis/dissertation must be in accordance with that legislation and must be properly acknowledged. Further distribution or reproduction in any format is prohibited without the permission of the copyright holder.

*To Sandra*

# Abstract

Climate change would likely pose significant challenges to agriculture. Previous assessments of the effect of climate change on agriculture show that developing countries are more vulnerable than developed countries. In this thesis, we contribute to the existing debate on the economic effects of climate change on land rents and production decisions. In the first chapter, we assess the capitalisation of climate change on land rental prices and net revenues of Mexican farms. Using cross-section data on the same farmsteads, we discover that using net revenues or land rental prices as measures of land rents in the Ricardian Hedonic model leads to different predictions. In the second chapter, we investigate how changes in climate would likely modify current crop and livestock choices in Mexico. Taking advantage of a plot-level dataset, we examine substitution patterns among arable and non-arable activities and find that accounting for such patterns in the discrete choice models leads to radically different projections. Taking climate change as an opportunity to produce food more efficiently, we use the Stochastic Frontier approach to assess the performance of Mexican farms in the third chapter. We find that farmers can produce more using the same amount of inputs, which can partially reduce or fully offset harmful effects of climate change.

## Acknowledgments

Many thanks to my supervisors Professor David Maddison and Professor Anindya Banerjee for their support. Without their wise guidance the quality of this thesis would not be the same. David, many thanks for always encouraging me to improve the quality of every single detail in this thesis. Your comments, academic and personal advice have changed the way in which I do conduct my own research. Anindya, thanks for all your comments about my work and for the unconditional support. I will always appreciate your help. To Steven Van Passel and Matthew Cole, the examiners of this thesis, thanks a lot for taking the time to read and provide constructive comments, I really enjoyed the VIVA.

I would like to thank the Economic and Social Research Council (ESRC) in the United Kingdom (UK) for their support. Thanks to the National Council of Science and Technology (CONACYT-reference 417254/384499) and the Ministry of Public Education (SEP-*Beca complemento*) in Mexico for providing funds that contributed to the development of this research project. I also express my gratitude to the ESRC, the Business School at the University of Birmingham (UoB), the Department of Economics at the UoB and the Agricultural Economics Society (AES) in the UK for their financial support to disseminate the main results of my research in international conferences.

The estimation of all empirical models in this thesis would not be possible without the data provided by the National Institute of Statistics and Geography in Mexico (INEGI). I express my deep gratitude to the people in the Microdata Laboratory, especially to Natalia Volkow and Liliana Martinez, and to those who collected high-quality data through the National Agricultural Survey in INEGI.

To my beloved and best friend Sandy, thank you very much for being part of the ups and downs of this long way. This thesis is also yours. I will always remember those days when the choice

models did not converge. You were always smiling and encouraging me to keep working on them. Once again, thanks a lot. This dream may not have come true if you were not there.

Despite the distance, my family has truly inspired me to accomplish this goal. They were the little voice telling me to keep going in the worst moments. *Ma* and *Pa*, I do not have words to thank you both for all you have done for me. Your sayings like ‘going to school is your job, so work hard’ and ‘the best inheritance that I have for you is your education’ inspired me to achieve this target, thanks. Irais and Susana, my beloved sisters, many thanks for your support and remember that you are always in my mind. *Las quiero mucho*. All my gratitude goes to my grandfather, who in spite of their beliefs, encouraged me to pursue my dreams.

I should like to say a big thank you to our friends who used to spend some time with us at home, Birmingham. Adolfo, thanks for showing us that a degree does not necessarily make us better than others. Allan, thanks for your useful academic and personal advice. Jose Manuel, I still remember the way in which you used to said hello to new Mexican fellows in Birmingham, including myself, many thanks for doing that. Jorge and Frida, thank you both for your friendship and sharing lots of good moments with us, especially those at Griffin House. Emanuel (*capi)*, thank you very much for all those talks about Mexico (the *4T*). I also express my gratitude to all friends that we met in Birmingham, especially to those who played football every Sunday, Gio and Ale.

# Table of Contents

# List of Figures

## Chapter 1



## Chapter 2



## Chapter 3



## Chapter 4

# List of Tables

## Chapter 2



## Chapter 3

## Chapter 4

# List of abbreviations

AEZ: Agro-Ecological Zone
APSIM: Agricultural Production Systems sIMulator
ATE: Average Technical Efficiency
CA: Control Area
CAP: Common Agriculture Policy
CCSM4: Community Climate System Model 4
CD: Cobb-Douglas
CDMX: Mexico City
CERES: Crop Environment Resource Synthesis model
CGCM3: Meteorological Research Institute Coupled General Circulation Model 3
CIAT: International Centre for Tropical Agriculture
CL: Conditional Logit
CLINO: climatological normal values
CO2: Carbon Dioxide
CONAGUA: National Water Commission
CONAPO: National Council of Population
CropSyst: Cropping Systems Simulation Model
DEA: Data Envelope Analysis
DSMW: digital soil map of the world
EPIC: Erosion Productivity Impact Calculator
FAO: Food and Agriculture Organization
FE: Fixed Effects
FIML: Full Information Maximum Likelihood
GCM: Global Climate Model
GDP: Gross Domestic Product
GHCN: Global Historical Climate Network Dataset
GIS: Geographic Information System
ICC: Indicative Crop Classification
IIA: Independence of Irrelevant Alternatives
INEGI: National Institute of Statistics and Geography in Mexico
IO: Input-Oriented
IPCC: Intergovernmental Panel on Climate Change
JLMS: Jondrow et al's formula
LFA: Less Favoured Area
LIML: Limited Information Maximum Likelihood

MIROC5: Model for Interdisciplinary Research In Climate 5
ML: Maximum Likelihood
MNL: Multinomial Logit model
MRTS: marginal rate of technical substitution
MXN: Mexican pesos
NAFTA: North American Free Trade Agreement
NAS: National Agricultural Survey
NL: Nested Logit model
NOAA: National Oceanic and Atmospheric Administration
NUTS: Nomenclature of Territorial Units for Statistics
OLS: Ordinary Least Squares
OO: Output-Oriented
PES: Payment for Environmental Services
RCP: Representative Concentration Pathways
RE: Random Effects
RIF: Recentered Influence Function
RTS: Returns To Scale
RUM: Random Utility Model
SAGARPA: Secretariat of Agriculture, Livestock and Rural Development, Fisheries and Food
SFA: Stochastic Frontier Analysis
SIAP: Agri-food and Fisheries Information Service
SIMBAD: State and Municipality Data System
SMN: National Meteorological Service
TE: Technical Efficiency
TI: Technical Inefficiency
TL: Translog
UN: United Nations
US: United States
USD: United States Dollars
VIF: Variance Inflation Factor
WRB: World Reference Base
WTP: Willingness to Pay

# Chapter 1 Introduction

Climate change is one of the most widely discussed issues. The Intergovernmental Panel on Climate Change (IPCC) states that changes in land uses and burning fossil fuels have increased[1] and will continue to increase the concentration of greenhouse gases in the atmosphere (IPCC, 2014). Rising greenhouse gas concentrations boosts the probability of trapping heat in the lower atmosphere. Thus, additional heat would warm the sea and, consequently, land surface temperature. Because there is so much uncertainty about future emissions, the IPCC assumes four different plausible scenarios for future emission trends, or Representative Concentration Pathways (RCPs), to project the most likely changes in surface temperature.

According to the National Oceanic and Atmospheric Administration (NOAA), the global Carbon Dioxide (CO2) concentration in early 2018 is of 408.96 parts per million (NOAA, 2018). From this concentration level, RCP2.6 assumes that annual emissions will reach a peak in 2020 and steadily decline in the 2020-2100 period. Under the RCP4.5 and the RCP6.0, the IPCC assumes that annual emissions will reach a peak in 2040 and 2080 respectively. Unlike other RCPs, the RCP8.5 assumes that annual emissions will rise until the end of the 21st century (IPCC, 2014). Implicitly, the abovementioned RCPs assume particular mitigation levels. From the scenario with higher mitigation levels (RCP2.5) to the no mitigation scenario (RCP8.5), the IPCC expects global mean surface temperature to increase between 1ºC and 3.7ºC by the 2081-2100 period (IPCC, 2014).

Global warming is expected to influence the hydrological cycle (Held and Soden, 2006). Increases in global temperature would likely cause higher evaporation rates, more clouds and more rainfall. However, it is widely agreed that there is a lot of uncertainty about changes in

[1] According to the IPCC Fifth-assessment report, land and sea surface temperature increased in average 0.85ºC in the 1880-2012 period.

rainfall patterns across the globe. Under such circumstances, projections of climate conditions differ from one zone to another and from one climate model to another (Mendelsohn and Dinar, 2009). In this regard, assessments of the potential impact of climate change on different sectors should take into account uncertainty about future climate.

Climate change would likely pose important challenges to humans. In Africa, the key risks are a high competition for water resources (e.g. De Wit and Stankiewicz (2006) or Taylor et al. (2013)), reductions in crop productivity (e.g. Schlenker and Lobell (2010)) and food security issues (e.g. Lobell et al. (2008)). River and coastal floods (e.g. Christensen and Christensen (2003)), health issues related to extreme heat (e.g. Patz et al. (2005)) and higher frequency of wildfires (e.g. Liu and Goodrick (2010)) would affect Europe. Asia would probably suffer from water and food shortages (e.g. Immerzeel et al. (2010)), higher mortality rates due to heat-related illnesses (e.g. Silva et al. (2013)) and flood damages (e.g. Hirabayashi et al. (2013)). Australia and the South of Asia would face significant changes in coral reef systems (e.g. Hoegh-Guldberg (1999)) and damages from coastal floods (e.g. Hughes (2003)). In North America, it is likely that a changing climate would increase the frequency of wildfires (e.g. Westerling et al. (2006)), mortality rates (e.g. Luber and McGeehin (2008)) and the size of damages from river and coastal floods (e.g. Ely et al. (1993)). Climate change would also cause a reduction in water availability (e.g. Arnell (1999)), food production and food quality in Central and South America (e.g. Wheeler and Von Braun (2013)).

Although climate change would have an impact on many sectors, agriculture has been widely recognised as one of the most vulnerable sectors. Nowadays, the Food and Agriculture Organization (FAO) of the United Nations (UN) predicts that the current global population of 7.6 billion would reach 11.2 billion in 2100 and states that 37% of earth's land surface is allocated to agriculture and grazing (FAO, 2018).[2] Under these circumstances, food supply should increase to meet the future demand for food. Recently, the FAO states that the world hunger started to rise again, from 777 million (in 2015) to 815 million (in 2016) undernourished people (FAO et al., 2017). Regarding the importance of the agriculture sector, it accounts for 4% of the world's Gross Domestic Product (GDP) and 27% of total employment (World Bank, 2018). In addition to this, Easterling et al. (2007) highlighted the importance of agriculture by arguing that this sector is the primary source of livelihood of two thirds of the rural population in the world. Under such circumstances, climate change would pose additional challenges to the agriculture sector.

The effect of climate change on agriculture can be observed through yield changes. Such changes may arise due to modifications in long-term temperature and rainfall, higher frequency of extreme events (e.g. droughts, floods or hurricanes), the onset of plagues and plant/animal diseases, etc. To assess the impact of climate change on agriculture, the existing literature offers a wide range of approaches, which include agronomic models (e.g. Adams et al. (1989) or Adams and McCarl (2001)), mathematical programming (e.g. Hertel (2011) or Nelson et al. (2014)), Ricardian analyses (e.g. Mendelsohn et al. (1994)) and other econometric approaches such as the estimation of production functions. Although we discuss the advantages and disadvantages of each method in more detail in the next chapter, agro-economic models are not able to account for farmers' adaptation strategies, the calibration of mathematical programming models is not straightforward and the level of data aggregation in mathematical programming models limits their capabilities to deal with farm-level information. Therefore, we focus our attention on those assessments that use the Ricardian Hedonic framework.

[2] From this figure, each person currently occupies 0.64 hectares of land in average.

Using the Ricardian Hedonic approach and the set of most likely scenarios for the corresponding regions,[3] previous studies predicted heterogeneous effects of climate change on agriculture. For instance, Masseti and Mendelsohn (2011) predict losses/gains between -5% and +12% of agricultural land values in the United States (US). Van Passel et al. (2017) encounter that European farms are more sensitive to global warming than US farms, depending on the climate change scenario predicted losses/gains vary from -32% to +5% of current land values. In Asia, Mendelsohn (2014) encounter that current crop net revenues would likely decrease/increase between -28% and +3% because of climate change. Regarding livestock in Africa, Seo and Mendelsohn (2008) predict average losses/gains between -25% and +168% of current net revenues. For arable activities in Africa, Seo et al. (2008) encounter a wider range of losses and gains; these values vary between -169% to +121% of the current net revenues. In South America, Seo and Mendelsohn (2007) find average losses between -62% and -15% of the current agricultural land values. Timmins (2006) predicts positive effects of climate change in Brazil, country that is not part of the Seo and Mendelsohn's (2007) investigation, between +0.88% and +13.8% of current land values. In contrast to Timmins' findings, Mendelsohn et al. (2010) and Galindo et al. (2015) predict average losses between -42% and -54% of land values and between -19% and -36% of net revenues in Mexican farms.

At the national level, agriculture GDP represents 3.29% of the total GDP of Mexico.[4] In terms of employment, the agriculture sector employs, in average, 6.47 million of workers in the 2005-2018 period, which represents 13.59% of the total labour force in Mexico. According to the 2014 National Agriculture Survey (NAS) released by the National Institute of Statistics and Geography (INEGI) in Mexico, the total area sown with the 26 major annual and perennial crops in the 2013-2014 agricultural year was 12.68 and 2.95 million of hectares, respectively.

[3] Typically, these studies use projected climate for 2100.
[4] We take the average of the 1993-2018 period. It goes from 3.56% in 1993 to 2.67% in 2018.

Thus, the total arable land comprises 15.63 million hectares. Maize, sorghum, beans, coffee, sugar cane and wheat account for 42.97%, 14.07%, 12.02%, 4.87%, 4.81% and 4.45% of the total area sown, respectively. In terms of average yields per hectare, we observe that Mexican farmers produce 3.4, 3.5, 0.8, 1.3, 68.8 and 5.1 tons per hectare, respectively.

Regarding livestock, the same survey finds that there exist 28.42 million of bovine animals (beef cattle) in Mexico. Most of the beef cattle production takes place in Veracruz (11.81% of the total number of animals), Jalisco (8.20%), Chihuahua (7.00%) and Durango (6.83%). For pigs, the same survey states that there exist 14.15 million of pigs in Mexico and that its production mostly takes place in Sonora (16.02%), Jalisco (12.85%), Guanajuato (8.38%) and Yucatan (7.45%). Regarding the number of poultry, the NAS reports that there are 399.89 million of animals and that Jalisco and Sinaloa concentrates the production of poultry. The production of poultry of these two states accounts for 21.25% and 16.73% of the total number of poultry in Mexico, respectively.

Hijmans et al. (2005) downscale Global Climate Model (GCM) data from the IPCC Fifth Assessment and publish a set of high resolution (~1 km$^2$ at the Equator) Geographical Information System (GIS)-databases, which comprises layers for different climate change scenarios. Figures 1.1a-1.1c show the current (1950-2000) and future (2061-2080) normal values of temperature in Mexico projected by the Community Climate System Model (CCSM4), the Model for Interdisciplinary Research In Climate (MIROC5) and the Meteorological Research Institute Coupled General Circulation Model (CGCM3) for the four RCPs. According to these figures, current average temperature (20.35ºC) is expected to rise between 0.6ºC-2.4ºC, 1.0ºC-3.3ºC, 1.2ºC-3.1ºC and 1.8ºC-4.5ºC assuming emission trends in RCP2.6, RCP4.5, RCP6.0 and RCP8.5 respectively.

Regarding rainfall patterns, Figures 1.1d-1.1e display the percentage change in future rainfall with respect to current normal values. The three GCMs predict both a wetter and a drier future for particular areas. In average, rainfall is expected to decrease between -1.55% and -12.35% by the end of the 21st century in Mexico. However, the range of the projected changes varies within the -47.52%-(+)31.15% interval. Therefore, the effect of climate change on agriculture in Mexico may not be homogenous and projections for the future of agriculture depend on the climate change scenarios and the geographical location of farms.

To cope with a changing climate in Mexico, the policy agenda mainly focus on mitigation strategies. The national government aims to reduce greenhouse gas emissions from agriculture and grazing through different means. According to the *'Agenda de transversalidad'* in FAO (2014), the Secretariat of Agriculture, Livestock and Rural Development, Fisheries and Food (SAGARPA) aims to incorporate 2.2 million hectares of arable and grazing land to the Payment for Environmental Services (PES) programme and to implement agri-environmental projects[5] in 61,995 hectares currently enrolled in the *'Programa de Apoyos Directos al Campo'* (PROCAMPO). Furthermore, SAGARPA aims to support farmers enrolled in the *'PROGAN productivo'* subsidisation programme to restore eroded fields by planting 353 million trees (30 plants per animal) and to carry out planned grazing in 5 million hectares. Among other strategies, SAGARPA also aims to reconvert 125 thousands hectares currently allocated to the production of maize (self-consumption practices) to forested areas.

[5] Agricultural practices that reduce the level of emissions or the use of chemical pesticides and fertilisers.

## Figure 1.1 Surface warming and change in rainfall patterns in Mexico (2061-2080)

**Figure 1.1a. Current temperature and CCSM-4 projections**

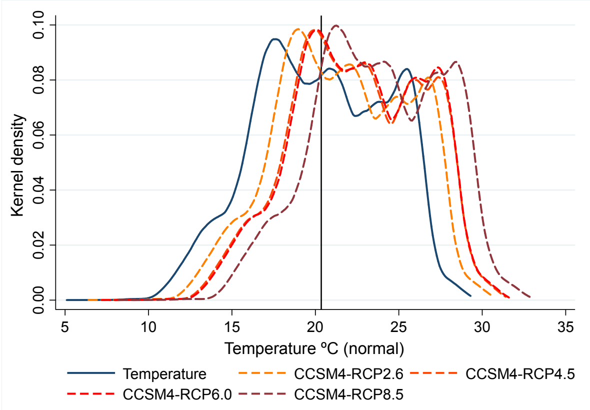



**Figure 1.1b. Current temperature and MIROC5 projections**

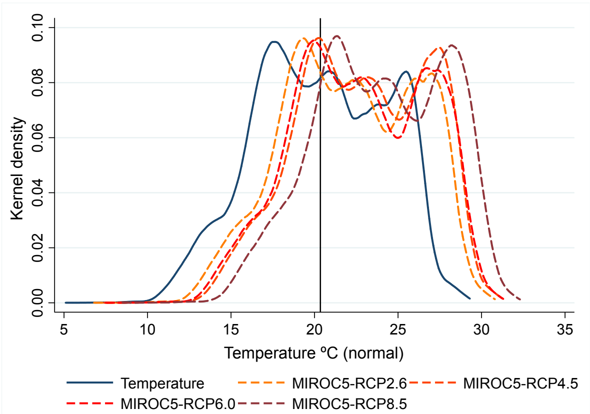



**Figure 1.1c. Current temperature and CGCM3 projections**

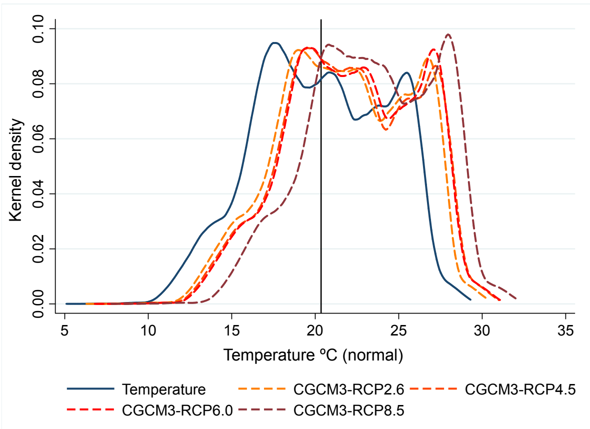



**Figure 1.1d. Change in rainfall from the CCSM-4 projections**

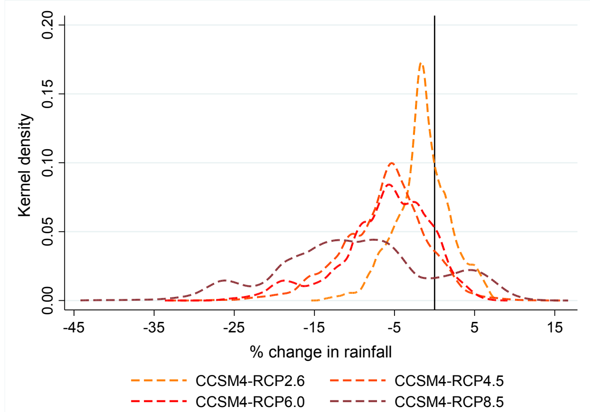



**Figure 1.1e. Change in rainfall from the MIROC5 projections**

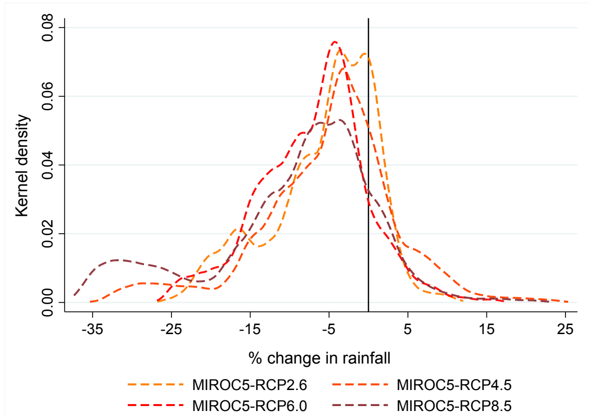
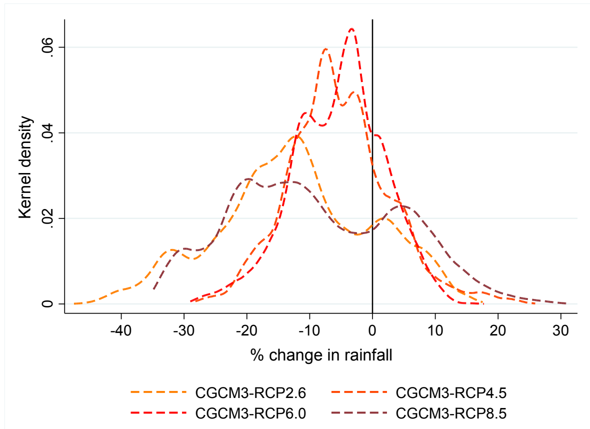



**Figure 1.1f. Change in rainfall from the CGCM3 projections**




Source: own elaboration based on Hijmans et al. (2005)

Note: we extract current and projected values of temperature and rainfall from the corresponding 10-minutes resolution GIS-databases in Hijmans et al. (2005). Using the value at the centroid of each cell, we obtain the distribution of current and future temperature from 3 GCMs, which provide projected values for each of the 4 RCPs in the IPPC fifth assessment. The vertical line represents the average of current temperature and the zero line in the rainfall graph. CCSM4: Community Climate System Model. MIROC5: Model for Interdisciplinary Research In Climate. MRI-CGCM3: Meteorological Research Institute Coupled General Circulation Model.

Uncertainty about future climate change may prevent policy-makers to provide a precise policy agenda for adaptation strategies in the agriculture sector. However, the policy agenda in

Mexico considers four general strategies to cope with or to reduce likely harmful effects of climate change on agriculture. First, innovations in production technologies and information. This policy includes the creation of technologies that facilitate the production of new crops, varieties and breeds that are more resistant to future climate and the installation of meteorological stations to generate timely climate/weather information. Second, institutional mechanisms that promote the sustainable management of water sources (needed for irrigation) and linking subsidy payments, e.g. PROGAN, to reforestation practices. Third, changes in agriculture practices such as crop diversification, switching to other crops, installing irrigation facilities and adjusting planting dates. Fourth, provide farmers with access to insurances, which can reduce the risk of catastrophic losses (FAO, 2014).

The existing literature recognises that crop/type of livestock switching and irrigation are powerful tools to help farmers to reduce harmful effects of climate change. Due to some crops or types of livestock may not be suitable for a different climate farmers should reallocate their production efforts to cultivate/harvest commodities that gives them the highest profits taking into account the new climate (Kurukulasuriya et al., 2008; Moniruzzaman, 2015; Ou and Mendelsohn, 2017). To cope with unreliable rainfall, previous studies argue that farmers should install an irrigation system to be less sensitive to future water shortages (Kurukulasuriya and Mendelsohn, 2011). Within this context, climate change also brings an opportunity to produce agriculture commodities more efficiently. Because of a changing climate, farmers should reallocate their production efforts and/or adjust their production processes in order to waste fewer resources and be more efficient. In other words, climate change may force farmers to use available (and scarce) resources more efficiently, which can partially reduce or totally offset harmful effects.

Taking into account the abovementioned discussion about likely effects of climate change on agriculture and the existing literature, this thesis contributes to the existing stock of knowledge as follows. In chapter 2, '*Are net revenues appropriate measures of land rents in Ricardian hedonic analyses?*', we assess the capitalisation of climate change on agricultural and grazing land values in Mexico. Unlike Mendelsohn et al. (2010) and Galindo et al. (2015), who use a small number of farms and municipal-level data respectively, we estimate a Ricardian Hedonic model to obtain implicit prices of temperature and rainfall using farm-level data on net revenues from a country-representative sample.[6] Moreover, using data on rental prices and net revenues from the same farmsteads, we examine the appropriateness of using net revenues in Ricardian Hedonic models to assess the impact of climate change on agriculture in development countries.

We argue that previous studies using net revenues as indicators of land productivity might be biased because net revenues are observed at the end of the agricultural year and are sensitive to annual weather rather than long-term climate. For instance, unexpected changes in rainfall patterns[7] during the growing season may partially damage or wholly destroy the annual harvest even if such land is highly productive. Furthermore, annual net revenues may suffer from measurement errors because typically farmers are not able to report annual revenues and costs properly, especially in developing countries where most of the farmers do not elaborate accounting records. Therefore, annual net revenues might not reflect land productivity (the Ricardian rent). The main findings in this chapter suggest that implicit prices of temperature and rainfall resulting from the rental price and net revenues models are statistically different.[8] Speculating about the effect of climate change on agriculture, we encounter that such differences lead to different assessments. Therefore, conclusions drawn from Ricardian Hedonic models using annual net revenues should be interpreted with caution.

---

[6] We also overcome other deficiencies in Mendelsohn et al. (2010) and Galindo et al. (2015) such as taking into account farms' heterogeneity by using a representative sample and controlling for soil characteristics in the Hedonic model (see the next chapter for further details).

[7] Deviations from their normal values (long-term averages).

[8] We use a set of F-tests that corroborate such finding.

In chapter 3, *'The effect of climate change on crop and livestock choices'*, we investigate the influence of climate change on crop and livestock choices. Using plot-level information on crop and livestock observed choices, we relax the Independence of Irrelevant Alternatives (IIA) property, which is assumed in previous studies using the Multinomial Logit (MNL) model, and estimate a Nested Logit model (NL) to predict the likely changes in crops and livestock choices under different climate change scenarios. We argue that the IIA property does not hold in this context because farmers' production choices are typically correlated, that is, the existence of new alternatives or the exclusion of existing alternatives have an effect on observed choices. For instance, if the production of beef cattle becomes a feasible alternative for a particular farmer, who initially planted maize and beans with equal probability, it is likely that this new alternative modifies the odd-ratio between maize and beans since maize is required as an input in beef cattle production. The IIA property assumes that if A= {Maize, 50%; Beans, 50%}, then the maize-beans odd-ratio=50/50=1 and if B= {Maize, 33.33%; Beans, 33.33%; Beef Cattle, 33.33%}, then the maize-beans odd-ratio=33.33/33.33=1. However, this is not likely to happen when maize is an input for beef cattle production. One would expect that the farmer would assign a higher probability to the production of maize with respect to the production of beans. In this regard, the NL model relaxes the IIA assumption and allows for correlation among similar alternatives or alternatives that can be jointly produced.

Unlike the existing literature, we also analyse likely transitions between particular arable and pastoral activities rather than analysing such activities separately. Given the spatial distribution of agricultural fields and the observed variation in prices, we also improve estimations in the existing literature by using the full set of expected farm-gate output prices in the choice equations rather than ex-post output prices. In contrast to previous studies and following theoretical underpinnings, we set cross-prices to zero in the choice equations because these values are not part of the corresponding profit function. After estimating both a MNL model, which has been widely used to speculate about the effects of climate change on crop and livestock choices in the existing literature, and a NL model, and replacing current with future climate in the corresponding agricultural fields, the main findings suggest that ignoring correlation patterns among alternatives leads to radically different conclusions. For some commodities, these models predict opposite results, that is, the NL (MNL) suggests that certain commodities will more (less) likely to be chosen because of climate change. For those crops or types of livestock for which both models predict a reduction (increase) in the average probability of selecting them, the size of such changes are, in most of the cases, different.

In chapter 4, *'PROCAMPO and farms' technical efficiency: a stochastic frontier analysis'*, we examine the association between agricultural subsidies and farms' technical efficiency. We argue that climate change brings an opportunity for farmers to avoid inefficient practices in the future. In this regard, the existing literature states that agricultural subsidies are one of the main factors preventing farmers to adopt efficient practices (Minviel and Latruffe, 2017). To examine such relationship and assess the performance of Mexican farms, we use farm-level data on farms producing annual crops to estimate a stochastic frontier model and compute farm-specific technical efficiency scores. These scores enable us to identify the main determinants of technical inefficiency in the agriculture sector in Mexico, where there is no a similar study.

We also contribute to the existing literature by computing farm-specific and percentile-specific estimates of the technical efficiency-subsidy relationship. Such estimations allow us to identify differential associations within the sample. We argue that the subsidy-farms' technical efficiency link is not monotonic, that is, the subsidy payments contribute to use available resources more efficiently in some farms while other farms become less efficient. To test whether this hypothesis holds in our data or not, we use Recentered Influence Function (RIF)-regressions and Wang's (2002) formula. The main findings suggest that there exist large inefficiencies in the production of annual crops, the size of the negative subsidy-technical efficiency association increases as inefficiency scores rise and few farmers use subsidy payments to be more efficient.

To identify the capitalisation of climate on land values in chapter 2, the effect of climate change on farms' choices in chapter 3 and the agricultural subsidies-farm's technical efficiency in chapter 4 of this thesis, we use two waves of the NAS released by the INEGI. These surveys are representative samples of the agriculture sector in Mexico and collected data on agriculture activities, facilities, equipment, labour and socio-demographic characteristics of the farmers in the 2011-2012 and 2013-2014 agricultural years. The two waves comprise information from 84,805 (258,217) and 65,692 (202,338) farms (plots of land) respectively. Interviewers and respondents used digital and printed maps for geographically locating all agricultural fields (plots of land) within the corresponding farms. Therefore, we can easily assign the corresponding climate, soil characteristics and other relevant variables to the sampled land.

For estimating a Ricardian Hedonic model, the 2012 NAS and 2014 NAS collects data on the total land rental payment and the rented area per farm, which allows us to compute the rental price per hectare. Furthermore, these databases comprise data on total output, farm-gate prices and utilised area per farm, which permits the computation of net revenues (total revenue minus non-land costs) per hectare. Taking advantage of the disaggregation of such datasets, the choice model uses mutually exclusive farmers' crop and livestock choices among 31 alternatives in each of their fields and treats them as discrete outcomes. Unfortunately, the 2012 NAS does not collect data on agricultural subsidies, while the 2014 NAS does. This prevents us to identify the effect of subsidies on crop/livestock choices and on farms' technical efficiency in the 2012 agricultural year. At the end of this thesis, in chapter 5, we provide a set of conclusions, limitations of this research, and potential areas for future developments.

## References


Adams, R., Glyer, J.D. and McCarl, B., 1989. The economic effects of climate change on US agriculture: a preliminary assessment. *The Potential Effects of Global Climate Change on the United States*, *1*, pp.4-1.

Adams, R.M. and McCarl, B., 2001. Agriculture: agronomic-economic analysis. *Global Warming and the American Economy: A Regional Assessment of Climate Change, Edward Elgar, Northhampton, MA*, pp.18-31.

Arnell, N.W., 1999. Climate change and global water resources. *Global environmental change*, *9*, pp.S31-S49.

Christensen, J.H. and Christensen, O.B., 2003. Climate modelling: severe summertime flooding in Europe. *Nature*, *421*(6925), p.805.

De Wit, M. and Stankiewicz, J., 2006. Changes in surface water supply across Africa with predicted climate change. *Science*, *311*(5769), pp.1917-1921.

Easterling, W.E., Aggarwal, P.K., Batima, P., Brander, K.M., Erda, L., Howden, S.M., Kirilenko, A., Morton, J., Soussana, J.F., Schmidhuber, J. and Tubiello, F.N., 2007. Food, fibre and forest products. *Climate change*, pp.273-313.

Ely, L.L., Enzel, Y., Baker, V.R. and Cayan, D.R., 1993. A 5000-year record of extreme floods and climate change in the southwestern United States. *Science*, *262*(5132), pp.410-412.

FAO, 2014. México: el sector agropecuario ante el desafío del cambio climático. Dirección de Políticas Públicas y Planificación Forestales. *FAO*, México.

FAO, 2017. FAOSTAT. Rome, Italy. From http://www.fao.org/faostat/en/#data/OA. 12 July 2018.

FAO, IFAD, UNICEF, WFP and WHO, 2017. The State of Food Security and Nutrition in the World 2017. Building resilience for peace and food security. Rome, *FAO*.

Food and Agriculture Organization FAO, 2018, July 17. Faostat: Land Use. Retrieved from http://www.fao.org/faostat/en/#data/RL.

Galindo, L.M. and Reyes, O., 2015. Climate change, irrigation and agricultural activities in Mexico: A Ricardian analysis with panel data. *Journal of Development and Agricultural Economics*, *7*(7), pp.262-273.

Held, I.M. and Soden, B.J., 2006. Robust responses of the hydrological cycle to global warming. *Journal of climate*, *19*(21), pp.5686-5699.

Hertel, T.W., 2011. The global supply and demand for agricultural land in 2050: A perfect storm in the making?. *American Journal of Agricultural Economics*, *93*(2), pp.259-275.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. and Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology*, *25*(15), pp.1965-1978.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H. and Kanae, S., 2013. Global flood risk under climate change. *Nature Climate Change*, *3*(9), p.816.

Hoegh-Guldberg, O., 1999. Climate change, coral bleaching and the future of the world's coral reefs. *Marine and freshwater research*, *50*(8), pp.839-866.

Hughes, L., 2003. Climate change and Australia: trends, projections and impacts. *Austral Ecology*, *28*(4), pp.423-443.

Immerzeel, W.W., Van Beek, L.P. and Bierkens, M.F., 2010. Climate change will affect the Asian water towers. *Science*, *328*(5984), pp.1382-1385.

IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. *IPCC*, Geneva, Switzerland, 151 pp.

Kurukulasuriya, P. and Mendelsohn, R., 2008. Crop switching as a strategy for adapting to climate change. African Journal of Agricultural and Resource Economics, 2(1), pp.105-126.

Kurukulasuriya, P., Kala, N. and Mendelsohn, R., 2011. Adaptation and climate change impacts: a structural Ricardian model of irrigation and farm income in Africa. *Climate Change Economics*, *2*(02), pp.149-174.

Liu, Y., Stanturf, J. and Goodrick, S., 2010. Trends in global wildfire potential in a changing climate. *Forest ecology and management*, *259*(4), pp.685-697.

Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P. and Naylor, R.L., 2008. Prioritizing climate change adaptation needs for food security in 2030. *Science*, *319*(5863), pp.607-610.

Luber, G. and McGeehin, M., 2008. Climate change and extreme heat events. *American journal of preventive medicine*, *35*(5), pp.429-435.

Massetti, E. and Mendelsohn, R., 2011. Estimating Ricardian models with panel data. *Climate Change Economics*, *2*(04), pp.301-319.

Mendelsohn, R., 2014. The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture*, *13*(4), pp.660-665.

Mendelsohn, R., Arellano-Gonzalez, J. and Christensen, P., 2010. A Ricardian analysis of Mexican farms. *Environment and Development Economics*, *15*(2), pp.153-171.

Mendelsohn, R., Nordhaus, W.D. and Shaw, D., 1994. The impact of global warming on agriculture: a Ricardian analysis. *The American economic review*, pp.753-771.

Mendelsohn, R.O. and Dinar, A., 2009. *Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects*. Edward Elgar Publishing.

Minviel, J.J. and Latruffe, L., 2017. Effect of public subsidies on farm technical efficiency: a meta-analysis of empirical results. *Applied Economics*, *49*(2), pp.213-226.

Moniruzzaman, S., 2015. Crop choice as climate change adaptation: Evidence from Bangladesh. *Ecological Economics*, *118*, pp.90-98.

National Oceanic and Atmospheric Administration NOAA, 2018, July 17. Global Greenhouse Gas Reference Network. Retrieved from https://www.esrl.noaa.gov/gmd/ccgg/trends/global.html.

Nelson, G.C., Van Der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H. and von Lampe, M., 2014. Agriculture and climate change in global scenarios: why don't the models agree. *Agricultural Economics*, *45*(1), pp.85-101.

Ou, L. and Mendelsohn, R., 2017. An analysis of climate adaptation by livestock farmers in the Asian tropics. *Climate Change Economics*, *8*(03), p.1740001.

Patz, J.A., Campbell-Lendrum, D., Holloway, T. and Foley, J.A., 2005. Impact of regional climate change on human health. *Nature*, *438*(7066), p.310.

Schlenker, W. and Lobell, D.B., 2010. Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, *5*(1), p.014010.

Seo, N. and Mendelsohn, R., 2007. *A Ricardian analysis of the impact of climate change on Latin American farms*. The World Bank.

Seo, S.N. and Mendelsohn, R., 2008. Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management 1. *Agricultural economics*, *38*(2), pp.151-165.

Seo, S.N., Mendelsohn, R., Dinar, A., Hassan, R. and Kurukulasuriya, P., 2008. *A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa*. The World Bank.

Silva, R.A., West, J.J., Zhang, Y., Anenberg, S.C., Lamarque, J.F., Shindell, D.T., Collins, W.J., Dalsoren, S., Faluvegi, G., Folberth, G. and Horowitz, L.W., 2013. Global premature mortality due to anthropogenic outdoor air pollution and the contribution of past climate change. Environmental Research Letters, 8(3), p.034005.

Taylor, R.G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y., Longuevergne, L., Leblanc, M., Famiglietti, J.S., Edmunds, M. and Konikow, L., 2013. Ground water and climate change. *Nature Climate Change*, *3*(4), p.322.

Timmins, C., 2006. Endogenous land use and the Ricardian valuation of climate change. *Environmental and Resource Economics*, *33*(1), pp.119-142.

Van Passel, S., Massetti, E. and Mendelsohn, R., 2017. A Ricardian analysis of the impact of climate change on European agriculture. *Environmental and Resource Economics*, *67*(4), pp.725-760.

Wang, H.J., 2002. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis*, *18*(3), pp.241-253.

Westerling, A.L., Hidalgo, H.G., Cayan, D.R. and Swetnam, T.W., 2006. Warming and earlier spring increase western US forest wildfire activity. *science*, *313*(5789), pp.940-943.

Wheeler, T. and Von Braun, J., 2013. Climate change impacts on global food security. *Science*, *341*(6145), pp.508-513.

World Bank WB, 2018, July 17. World Development Indicators. Retrieved from http://databank.worldbank.org/data/source/world-development-indicators.

# Chapter 2 Are net revenues appropriate measures of land rents in Ricardian hedonic analyses?

N.B. To improve the quality of this research, I presented previous versions of this chapter at the following conferences:

- June 2017. XVIII World Congress of the International Economic Association (IEA). Mexico City, Mexico.
- October 2016. 4th Annual Nottingham-Birmingham-Warwick ESRC DTC conference. Nottingham, United Kingdom. [https://www.nottingham.ac.uk/esrc-dtc/documents/2015-conference-presentations/saul-basurto-hernandez-esrc.pdf]
- June 2016. 22nd Annual conference of the European Association of Environmental and Resource Economists (EAERE). Zurich, Switzerland. [https://www.ethz.ch/content/dam/ethz/special-interest/conference-websites-dam/eaere-2016-dam/documents/EAERE_job-market-papers_ord.pdf
- May 2016. PhD Colloquium on Environmental and Energy Economics and Management. Birmingham, United Kingdom.
- April 2016. 5th Annual conference of Mexican fellows in Europe. Strasbourg, France.
- April 2016. 90th Annual conference of the Agricultural Economics Society (AES). Warwick, United Kingdom. [http://ageconsearch.umn.edu/record/236362/files/Saul_Basurto%20Hernandez_AES%20A%20Mexican%20Ricardian%20analysis%20S.pdf ]

In some cases, the organisers of such conferences made these versions public as part of the conference proceedings. I also presented a previous version of this work as my PhD research proposal. I am wholly responsible for the literature review, collection of the data, empirical analysis and interpretation of the results.

## 2.1. Introduction

Ricardo (1817) states that *'[land] rent is that portion of the produce of earth, which is paid to the landlord for the use of the original and indestructible powers of the soil'* (chapter 2). From this definition, Ricardo (1817) argues that population growth increases the demand for food, which at the same time (and without technological progress) leads to higher demand for land. The main argument of his seminal work is that marginal lands (less fertile lands) are putting into cultivation because of the increasing demand for food. Under such circumstances, [land] rent or *'the portion of the produce of earth'* varies among different lands and depends on their fertility or *'the original and indestructible powers of the soil.'*

Arguing that land is a differentiated factor of production, as in Ricardo (1817), Palmquist (1989) develops a hedonic model for the demand for agricultural land. Palmquist argues that landowners and tenants determine rental prices in the market based on land's attributes. In the hedonic framework, developed by Rosen (1974) and Freeman (1974), the more desirable the set of land attributes are, the higher the willingness to pay (rental price) for a particular plot of land and vice versa. More recently, Mendelsohn et al. (1994) combine the definition of land rents in Ricardo (1817) and the hedonic approach, as in Palmquist (1989), to assess the impact of climate change on agriculture. This approach treats climate as an additional land's attribute and is widely known as the Ricardian hedonic method.[9] Thus, welfare analyses using this approach look at the capitalisation of climate change on Ricardian land rents.

Several studies assessing the effect of climate change on agriculture in developing countries use annual net revenues as proxy variables of land values and productivity in the Ricardian hedonic framework (see for example Mendelsohn et al. (2001), Seo and Mendelsohn (2008a),

[9] The Ricardian hedonic model regresses land rents per unit of land on a vector of land's attributes such as climate, the characteristics of the soil and other control variables. It is usually a linear regression of land rents on a set of land's characteristics, and sometimes, it uses a log-linear functional form.

Gebreegziabher et al. (2013), Wang et al. (2014), Abidoye et al. (2017) and Batsuuri and Wang (2017)). Following Palmquist (1989), these studies define net revenues as the difference between the value of total output and non-land costs. This strand of literature argues that reliable measures of land values are not often available in developing countries because land markets do not operate properly and thereby net revenues, which are typical available, should be used.

In this chapter, we argue that net revenues may not accurately measure land rents in Ricardian hedonic models. On the one hand, net revenues are sensitive to unexpected events occurring during the agricultural year and may not precisely reflect the Ricardian rent. Consequently, implicit prices of land features drawn from such estimations might be biased. On the other hand, landowners and tenants determine rental prices of agricultural land based on their expectations and prior knowledge about land productivity on a medium-term basis. Under such circumstances, rental prices are not sensitive to unexpected events and may measure land rents more precisely.

Having this in mind, this chapter attempts to answer the following research questions: Do the implicit prices of land attributes (climate) differ by using land rental prices or net revenues in the Ricardian hedonic model? If so, what are the implications for assessing the effects of climate change on agriculture? This is worthy of investigation because the comparison between both Ricardian models allows us to validate or cast doubts on previous assessments, especially in developing countries. By answering such questions, we contribute to the existing literature by comparing implicit prices of climate resulting from the net revenues and rental prices hedonic models for the same farmsteads. We argue that rental prices and net revenues are comparable because these values represent annual measures of land productivity. The key difference between such measures is the time in which we observe them. We observe the former at the beginning of the agricultural cycle while the latter becomes apparent at the end of the agricultural cycle.

The Ricardian model identifies the capitalisation of climate on land values by looking at their variation throughout different territories. Under such circumstances, empirical studies require either a large sampled area or a relatively small area with high variation in altitude. Mexico meets the two-abovementioned prerequisites. Regarding the extent of the territory, the total area of Mexico is 1.97 million $km^2$, which is equivalent to eight times the size of the United Kingdom or one fifth of the total land surface of Europe. The National Institute of Statistics and Geography (INEGI) publishes a Geographical Information System (GIS)-database that contains information on different land uses, including arable land and areas with pastures (see Figure 2.1a). One can observe that agriculture activities take place along the entire territory.

Matching this information with Hijmans et al's (2005) data,[10] we observe that Mexican farmers carry out such activities under a wide range of temperature, rainfall and altitudes. According to Figure 2.1b, the 1970-2000 (average) annual temperature varied between 6.2ºC and 29.5ºC in arable land and areas with pastures. Using data on rainfall, Figure 2.1c shows that the range of the 1970-2000 (average) annual rainfall goes from 51 mm. to 4,757 mm. per year in the same areas. For the variation in altitude, Figure 2.1d displays the number of metres above the sea level (masl) of the corresponding areas. It shows a high variation in altitude along arable and pastoral areas. Farmers use fields located between -11 masl and 3,857 masl.

Apart from the large variation in climatic conditions throughout Mexico, which permits the cultivation (production) of a large variety of crops (types of livestock), the INEGI releases two-waves of cross-sectional data on agricultural activities at the plot level. Taking advantage of such information, we aim to improve previous estimations in the existing literature on crop and

[10] Using the GIS polygons dataset in Figure 2.1a, we extract the corresponding values of annual temperature, rainfall and altitude in Hijmans et al. (2005)

livestock choices by using plot-level rather than farm-level data. By using this data, we can include a large set of agricultural commodities in the analysis, which is not always possible in other countries with high levels of specialisation. Therefore, the agriculture sector in Mexico meets the prerequisites to estimate a Ricardian Hedonic model.

To answer the aforementioned research questions and test whether the implicit prices of climate are identical regardless of the use of net revenues or rental prices, we use cross-sectional data on 2,388 (573) and 5,301 (1,538) farms that rented at least one plot of land (farms with 100% rented land) in Mexico in the 2012 and 2014 agricultural years.[11] All these farms report rental prices and information needed to compute net revenues in the National Agricultural Survey (NAS).[12] Regarding climate, we extract long-term averages of temperature and rainfall from the 30 arc-seconds (~1 $km^2$) resolution Geographical Information System (GIS)-databases released by Hijmans et al. (2005). Additionally, we complement the set of climate variables using data from 3,388 meteorological stations. Also included in the Ricardian model are the soil types of the agricultural fields. These soil profiles come from the GIS-database published by INEGI (2014a), which is based on the *Soil map of the world* (FAO-UNESCO, 1997). Following previous studies, we also account for irrigation, land tenure, farmland area, access to electricity, road density, distances to nearest river, nearest water body and nearest city.

[11] For farms with at least one rented plot, we assume that if the rent were paid for owned lands, this rent would be similar to the rent (per unit of land) the farmer is paying for renting additional land. We relax this assumption by also using farms with 100% rented land in the analysis.

[12] Farm-level data is not publicly available. We access this data through the Microdata laboratory in the National Institute of Statistics in Mexico (INEGI). This guarantees confidentiality of information provided by the corresponding respondents, which is part of the INEGI's proceedings.

**Figure 2.1 An overview of climate in arable land and pastures in Mexico**

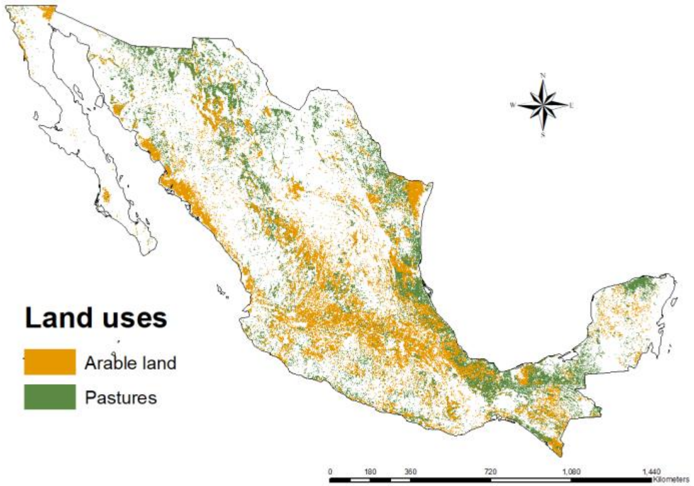



**Figure 2.1a Arable land and pastures**

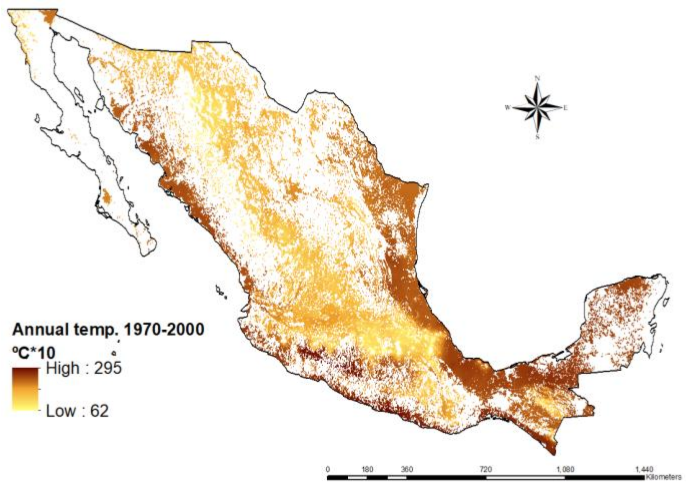



**Figure 2.1b Annual temperature 1970-2000**

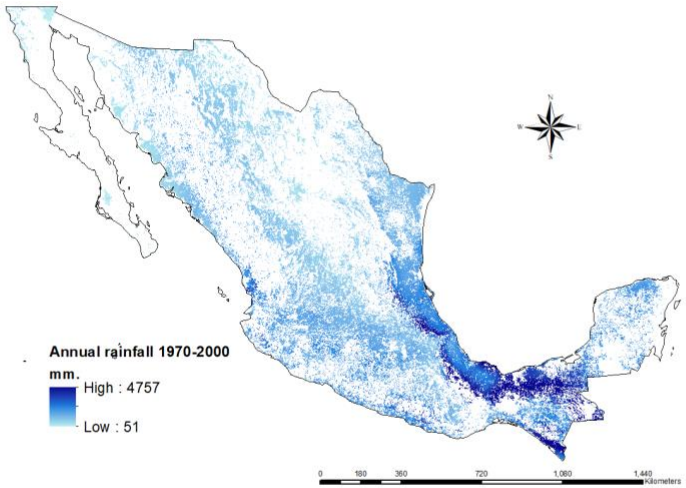



**Figure 2.1c Annual rainfall 1970-2000**

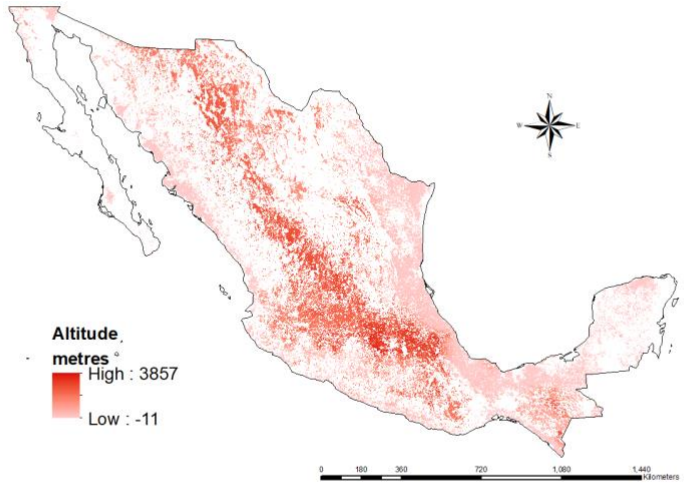



**Figure 2.1d Altitude (metres above the sea level)**

The main findings suggest that implicit prices of temperature and rainfall resulting from the rental price and net revenues Ricardian models are individually and jointly different. The implicit prices of one additional degree Celsius fluctuate between -16% and +18% (-18% and 21% in farms with 100% rented land) of the current rental price per hectare in farms with at least one rented plot while these implicit prices vary between -113% and +109% (-270% and 228%) of current net revenues per hectare. Moreover, the implicit price of an additional mm. of rain ranges from -0.16% to +0.08% (-0.44% and +0.13%) and from -0.26% to +0.71% (-0.47% and +0.53%) of rental prices and net revenues respectively. According to our theoretical model, these divergences arise because farmers maximise expected profits at the beginning of the agricultural year and pay rents accordingly.[13] However, unexpected variation in prices, weather and other events lead to deviations between expected net revenues[14] and actual net revenues.

Using predictions from three Global Climate Models (GCMs), we replace current with future climate in the Ricardian hedonic model and estimate the total cost of climate change for farms in both years. Interestingly, we encounter that net revenues and rental prices lead to different conclusions. For farms with at least one rented plot (with 100% rented land) in the 2012 sample, a warmer and drier future would likely change current net revenues between -$2,074 and -$557 (-$15,799 and +$241) Mexican pesos per hectare and current rental prices between +$192 and +$844 (+$146 and +$1,347) Mexican pesos per hectare. Regarding the 2014 sample, the net revenues model predicts a gain between +$3,989 and +$10,814 (+$5,798 and +$13,837) Mexican pesos per hectare while the rental price model predict losses/gains between -$64 and

[13] In Mexico, it is customary that tenants pay rents at the beginning of the agricultural cycle.
[14] Following Palquist (1989), expected net revenues should be equivalent to land rents (rental prices).

+$41 (-$207 and -$32) Mexican pesos per hectare. Since we use data on the same farmsteads, these results have important implications for future studies, especially in developing countries.

The remainder of this chapter is as follows. Section 2.2 comprehensively analyses the existing literature assessing the effects of climate change on agriculture via Ricardian hedonic models. In section 2.3, we use a simple theoretical model to show under which circumstances estimations from the two aforementioned Ricardian models are (not) equivalent. We also describe the Ricardian hedonic methodology and the set of variables in both models. Section 2.4 presents the set of findings related to implicit prices of climate and speculates about the effect of climate change on agriculture in Mexico. Section 2.5 concludes and provides a list of areas for further research.

## 2.2. Literature review

This section presents a literature review on previous studies assessing the effect of climate change on agriculture using the Ricardian hedonic model. For presentation purposes, we organise the review as follows. First, subsection 2.2.1 presents the literature survey. In subsection 2.2.2, we present an overview of empirical findings of Ricardian hedonic models using land values, rental prices, and net revenues as indicators of Ricardian land rents. Based on the literature review, subsection 2.2.3 briefly describes additional methodological issues of the Ricardian hedonic framework identified in the existing literature.

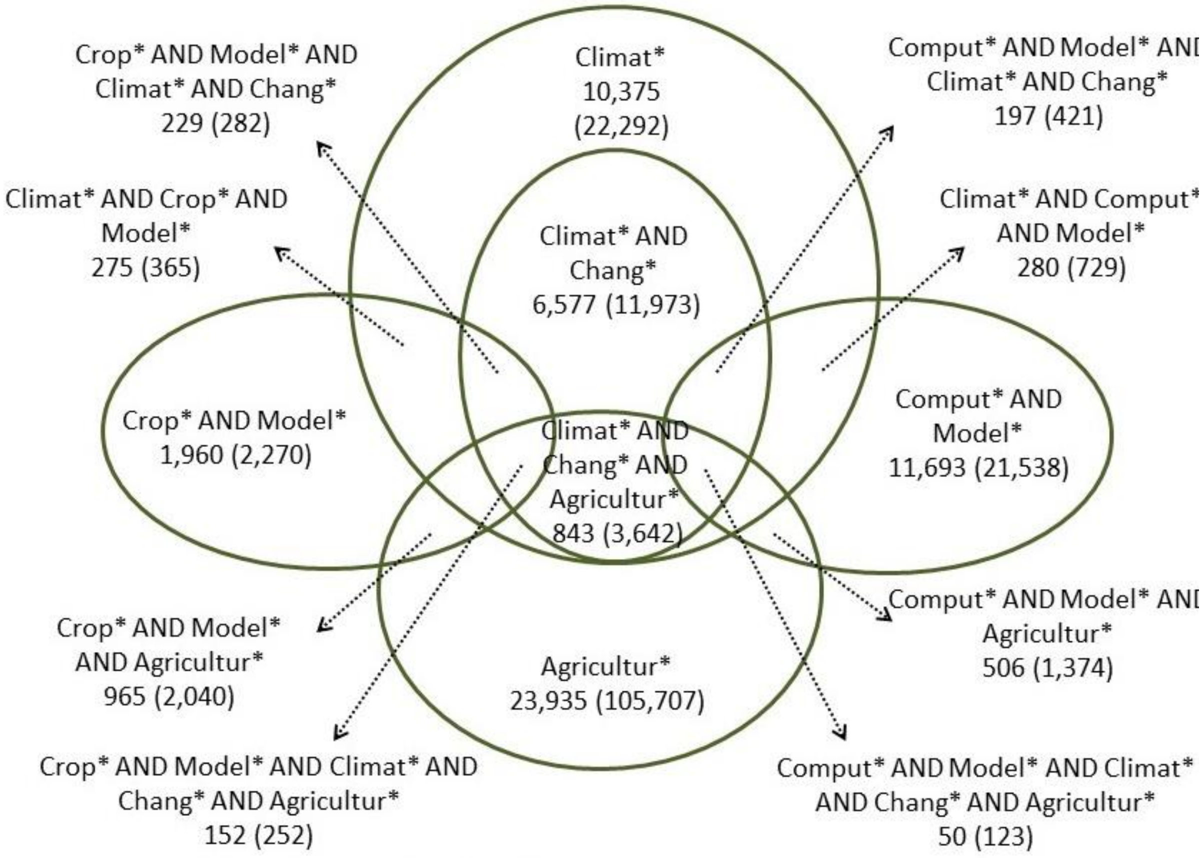
### *2.2.1. Literature survey*

Nowadays, there are several academic articles identifying the effects of climate change on agriculture. We explore such information through the following steps. First, we select a set of key words that helps us to efficiently surveying the literature: *climate change, agriculture, hedonic, Ricardian, crops, livestock* and *model*. Second, we use the following databases to identify relevant materials: *EconLit,* the *World Bank e-library* and the *Google Scholar* tool.[15] Third, we select the best outcome, set of papers and books, resulting from an initial search in *EconLit*, and then a comparison between this set of documents and the outcomes from the *World Bank e-library* and the *Google Scholar* tools allows us to incorporate additional materials. The outcomes from the three sources reveal the importance of our topic. There are more than 3,642 documents analysing climate change and agriculture.[16] Using the full set of key words and refining our search, figure 2.2 displays the outcome from the EconLit database. It suggests that 152 (252 in the text) and 50 (123 in the text) academic documents mention agronomic[17] and computable general equilibrium models in their abstracts, respectively. Although, there are some research works in the existing literature using agronomic and computable general equilibrium models to analyse the effect of climate change on agriculture, such approaches are out of the scope of this research.[18]

---

[15] Although, the Google Scholar database may be criticized because it considers several non-scientific documents, this database represents an upper bound for the number of documents related to our topic.
[16] We use the following search criteria: climat* AND chang* and agricultur* appearing anywhere in the text in EconLit (3,642 documents) and Google Scholar (4,421 documents). Climate change AND agriculture appearing in the title in Google Scholar (3,840 documents). Asterisks allow for any combination of letters at the end of each word.
[17] The key word agronom* seems to be ambiguous, thus, it was interchanged for crop*.
[18] See Appendixes A2.1 and A2.2 for a brief description of the agronomic and computable general equilibrium models. We highlight the weaknesses of these approaches and briefly explain why we do not use them in this chapter.

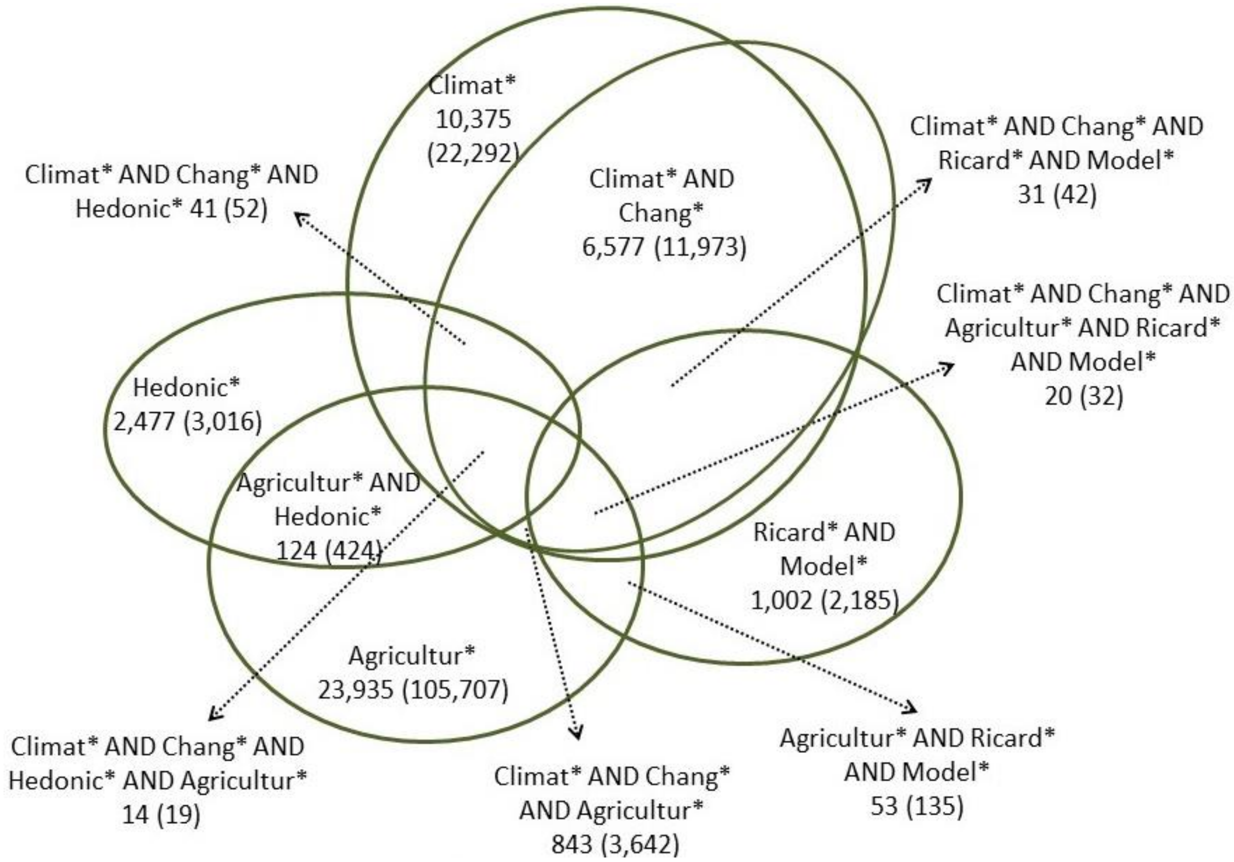
**Figure 2.2 Literature survey on climate change and agriculture**




Notes: number of articles in which the searching criteria appear in the abstract (appearing in the text in parentheses)
Source: own elaboration based on outcomes from EconLit

Refining further our search, figure 2.3 shows different combinations of the searching criteria. It shows that 53 documents analyse agriculture issues using the Ricardian framework. Furthermore, 31 entries include the keywords climate change and Ricardian model in their abstracts. By combining climate change, hedonic and agriculture terms, we encounter 14 additional research works. After joining the three sets of papers, the set of references from EconLit comprises 58 different published, working papers, chapters of books, technical reports, and books.

**Figure 2.3 Literature survey on Ricardian hedonic models**




Notes: number of articles in which the searching criteria appear in the abstract
(appearing in the text in parentheses)
Source: own elaboration based on outcomes from EconLit

From the EconLit set of materials, we remove eight irrelevant documents, five articles appear more than once in the surveyed literature, seven are critiques and comments about the Ricardian method and 36 articles are empirical applications of the Ricardian hedonic method. By using the same search criteria as in EconLit, we add 11 additional documents[19] from the World Bank e-library and Google Scholar sources.[20]

[19] These are case studies (empirical studies).
[20] Along this chapter, we include complementary materials dealing with different issues such as agronomic models, computable general equilibrium models, property rights, cross-references, etc.

### *2.2.2. Literature review: Ricardian studies*

To measure land rents in the Ricardian approach, the existing literature uses either land values/prices, rental prices or net revenues. Because the main purpose of this research is to investigate whether rental prices or net revenues perform better in the Ricardian model, we organise the literature review by grouping articles together depending on which of the abovementioned variable is used to measure land rents. This classification allows us to compare the advantages and disadvantages of the corresponding indicators.

#### *2.2.2.1. Land prices*

Mendelsohn et al. (1994) argue that, under perfect competition, farmland sale prices are equal to the present value of all future land rents. Moreover, if the interest rate and the rate of return of land are the same for all parcels, the land rent is proportional to the land price. Reinsborough (2003) and Garcia and Viladrich Grau (2009) argue that land values are accurate measures of land rents when land is allocated to its optimal use. Under such assumptions, researchers can use land prices as measures of the Ricardian rent.

The main advantages of using land values over other indicators are twofold. First, since land values are equal to the sum of future land rents when land is allocated to its optimal use, land values account for farmers' adaptation strategies. Second, land values are not sensitive to short-term conditions, e.g. weather shocks. Notwithstanding, we encounter some undesirable properties of land values. The fact that land values reflect the sum of future land rents implies that land uses other than agricultural activities are also part of such values, e.g. retirement homes.[21] Furthermore, land values are typically self-reported valuations in the existing

[21] Theoretically, sale prices already anticipate climate change since it is assumed that land is allocated to its optimal use even under different climates (Mendelsohn et al., 1994). In this regard, farmers' adaptation is implicitly accounted for in the Ricardian Hedonic models using sale prices.

literature, which may not reflect the value of land precisely. Many studies use average land values for census track areas rather than for individual farms. Such aggregation hides farms' heterogeneity and may lead to biased assessments (Timmins, 2006; Fezzi and Bateman, 2015). There are few empirical analyses for developed countries in which Ricardian analyses use actual farmland sale prices (see for example Palmquist and Danielson (1989) or Maddison (2000)). Another disadvantage is that land values are not typically available in developing countries, where most of the harmful effects of climate change would likely take place.

To identify how climate is capitalised in land values, empirical studies assume that variations in the climate across space partially explain the variation of land values. Most of the Ricardian studies define climate as the long-term (annual or seasonal) average of temperature and rainfall[22] in the corresponding plots. Table 2.1 presents an overview of empirical findings in the existing literature using land values. Previous assessments use climate change scenarios from different climate models and in some cases assume that climate would change homogeneously in the studied area to speculate about the effect of climate change on agriculture. Direct comparisons of such speculations among different regions/countries could be cumbersome therefore, we use implicit prices (calculated at sample means) of temperature and rainfall to analyse the set of previous findings.[23]

Table 2.1 shows that implicit prices of climate variables differ among seasons and places. For example, Mendelsohn and Nordhaus (1992) encounter that one additional degree Fahrenheit in January and July would reduce the value of land by \$86 and \$151 United States Dollars (USD)

[22] Few studies use degree-days (the cumulated number of degrees above a certain threshold) rather than normal values. Massetti et al. (2015) show that normal values and degree-days are interchangeable in the growing season and lead to similar results. This is not necessarily true for the non-growing season, where parameter estimates may lead to flawed conclusions. Normal values of temperature and rainfall are 30 or 50 years averages.
[23] We include those studies that report implicit prices of climate variables. Some studies do not report implicit prices and are not included in this table. However, the reader should refer to the Appendix A2.3 for an overview of all studies. This also applies for studies using rental prices and net revenues.

per acre while if this change takes place in April and October it would increase the value of land by $9.58 and $165 USD per acre respectively. To have a better idea about the size of these changes in land values, we look at the average value of land in the corresponding studies. Not all studies report the mean value of the dependent variable. For those that report the mean, we can see that implicit prices also vary from one study to another. For instance, an additional degree Celsius in the United States leads to a reduction on land values of 26% and 31% in winter and summer seasons and this change would increase land values by 21% and 35% in spring and autumn seasons respectively. An additional mm. of rainfall benefits land values in all seasons except in autumn. In Europe, Van Passel et al. (2017) find a statistically insignificant effect of temperature on land values. However, these authors encounter that an extra centimetre of rainfall per year may rise the value of agricultural land by €137 per hectare, which represents 0.86% of the average value (€16,000).[24]

There is one study analysing the effect of climate on land values in Mexico. Mendelsohn et al. (2010) conduct a cross-sectional Ricardian analysis using survey data for the 2002 agricultural year. This data comprises self-reported land values from 621 rural households (farms). Climate data comes from the National Meteorological Service (SMN) and includes the seasonal 30-years normal of temperature and rainfall.[25] Furthermore, the Ricardian model also accounts for differences in the characteristics of the soil by including soils' profiles from *the digital soil map of the world (DSMW) 2003.*

[24] See Table 2.1 for the corresponding implicit prices of climate variables in Brazil, South America, and England.
[25] The average of daily temperature and rainfall from 1970 to 2000.

## Table 2.1 Land values and implicit prices of temperature and rainfall

| Source | Place | Period | Units of analysis | Functional form | Dependent variable | Climate and margins (implicit prices)+++ |
|---|---|---|---|---|---|---|
| Mendelsohn and Nordhaus (1992) | United States | 1982 | 2,939 counties (crops) | Linear-linear | Self-reported value of land and buildings per acre | Change in value of land ($USD/acre)<br>Temp. January (1 ºF): -86***<br>Temp. April (1 ºF): 9.58<br>Temp. July (1 ºF): -151***<br>Temp. October (1 ºF): 165***<br>Rain. January (1 inch): 50***<br>Rain. April (1 inch): 109***<br>Rain. July (1 inch): 4.18<br>Rain. October (1 inch): -57*** |
| Maddison (2000) | England | 1994 | 405 transactions of farmland | Log-linear | Price per acre (mean=£2,642) | Change in land prices (£/ha) +<br>Temperature summer (1 ºC): -884<br>Temperature winter (1 ºC): 485<br>Rainfall summer (1 mm): -1.15<br>Rainfall winter (1 mm): 1.44 |
| Mendelsohn et al. (2001) | Brazil | 1970, 1975, 1980, 1985 | 3,941 municipalities | Log-linear | Self-reported land values per hectare | Change in land values ($USD/ha) +<br>Temperature (1970-1975/1ºC): -41.3<br>Temperature (1980-1985/1ºC): -19.4<br>Rainfall (1970-1975/1mm): 1.6<br>Rainfall (1980-1985/1mm): 1.1 |
| Timmins (2006) | Brazil | 1985 | 3,177 municipalities | Log-log | Average value of land per hectare (mean=0.96-12.45) | Change in average land value (%)+<br>Rain. summer (1 cm): 1.81-2.54<br>Rain. winter (1 cm): 4.76-8.14<br>Temp. summer (1 ºC): 3.84-11.60<br>Temp. winter (1 ºC): -5.95-1.99 |
| Seo and Mendelsohn (2007) | South America | 2004 | 2,035 farms | Linear-linear | Self-reported land values per hectare | Changes in land values ($USD/ha)<br>Temperature (1 ºC): -175.28**<br>Rainfall (1 mm): -30.37** |
| Seo and Mendelsohn (2008c) | South America | 2004 | 2,035 farms | Linear-linear | Self-reported land values per hectare (mean=$1,200-$6,000) | Change in land values ($USD/ha) +<br>Temperature (1 ºC): -76<br>Rainfall (1 mm): -22.5 |
| Mendelsohn et al. (2010) | Mexico | 2002 | 621 farms | Log-linear | Self-reported land values per hectare (mean=$27,100) | Change in land values ($MXN/ha)<br>Temp. winter (1 ºC): 586<br>Temp. spring (1 ºC): -11,497***<br>Temp. summer (1 ºC): -961<br>Temp. autumn (1 ºC): 4,181<br>Rain. winter (1 mm/mo): -923***<br>Rain. spring (1 mm/mo): 210<br>Rain. summer (1 mm/mo): 526***<br>Rain. autumn (1 mm/mo): -775*** |
| Massetti and Mendelsohn (2011) | United States | 1978, 1982, 1987, 1992, 1997, 2002 | 2,939 counties | | Self-reported value of land and buildings per hectare | Change of land value (%)<br>Temp. winter (1 ºC): -26.4***<br>Temp. spring (1 ºC): 21.1***<br>Temp. summer (1 ºC): -31.4***<br>Temp. autumn (1 ºC): 35.3***<br>Change of land value (%)<br>Rain. winter (1 mm): 0.46***<br>Rain. spring (1 mm): 0.35<br>Rain. summer (1 mm): 0.47***<br>Rain. autumn (1 mm): -0.73*** |
| Massetti et al. (2015) | United States | 1982, 1987, 1992, 1997, 2002, 2007 | 2,405 counties | | Self-reported value of land and buildings per hectare (mean=$3,950-$7,600) | % change of land value<br>Temperature: -15.9***<br>Degree days 8-32: -16.3*** |
| Van Passel et al. (2017) | Europe | 2007 | 37,612 farms (crops and livestock) | Log-linear | Land values per hectare based on observed prices in the region (mean=€16,000) | Change in land values (€/ha)<br>Temperature (1 ºC): 111<br>Rainfall (1 cm/mo): 137*** |

***, ** and * statistically significant at 1%, 5% and 10% significance level respectively
+ test for significance not reported, ++ bold numbers indicate that the marginal effect is significant at the 10%
+++Marginal effects evaluated at means.

The parsimonious model includes linear and square terms of seasonal temperature and rainfall, interaction terms, diurnal temperatures,[26] cropland, cropland square, a dummy variable for irrigation, the distance from the farm to the nearest city, altitude, and 6 soil types.[27] The full model indicates that farmers' characteristics are not relevant, e.g. experience, education and access to finance. Strictly speaking, farmers' characteristics (socio-demographic characteristics) must not be part of the hedonic regression since such variables are not land attributes.

The main results in Mendelsohn et al. (2010) suggest that a warmer and wetter future may reduce land values in Mexico. Using three different scenarios for 2100,[28] these authors estimate average losses of land values between 42% and 54%. Such predictions differ between small and large farms and irrigated and rain-fed farms. Regarding implicit prices, Table 2.1 indicates that one additional degree Celsius in spring reduces land values by $11,497 Mexican Pesos (MXN) (-42%). Other seasonal effects are not statistically significant. An additional mm. of rainfall may reduce land values by $923 (3.41%) and $775 (2.86%) in winter and autumn respectively, while it may rise the value of land by $526 (1.94%) in summer. Mendelsohn et al. (2010) derive their conclusions from a small sample of farms that are not by any means representative of the agriculture sector in Mexico. The 621 farms are located in rural areas from 14 states (out of 32 states) and are a subsample of the 1,765 interviewed households, which report some crop production. Furthermore, self-assessments of land values may not accurately measure the actual value of the corresponding lands because land transactions in rural areas in Mexico do not take place very often. Therefore, farmers in Mendelsohn et al's (2010) sample might not have enough/precise information and experience to value their lands properly.

[26] Difference between the maximum and minimum daily temperatures (normal values).
[27] Acrisol, Gleysol, Lithosols, Kastanozems, Nitosols and Xerosols.
[28] PCM, MIMR and HAD scenarios.

#### *2.2.2.2. Rental prices*

The main advantage of using rental prices to assess the capitalisation of climate change on land rents is that these prices are not sensitive to unexpected events occurring during the agricultural year[29] and compared to land prices they are not affected by future expectations.[30] Since farmers and landowners sign rental agreements and pay rents at the beginning of the agricultural year, independently of what would occur during that year, rental prices may better reflect land rents than other annual measures of economic rents, e.g. net revenues. It is also acknowledge that rental agreements may not precisely reflect Ricardian rents if an attribute of the land changes and the rental price does not change accordingly due to the length of the current lease (medium-term or long-term leases). For instance, if the government subsidises the installation of irrigation facilities in a specific year, which cannot be postponed, and the renegotiation of the rental agreement takes place in later years, this improvement will not be capitalised immediately in the current rental price. In Mexico, this is very unlikely since it is customary to negotiate rental prices every year and most of the land attributes change over long periods of time, e.g. climate change or soil erosion.

Although Lang (2007) argues that rental prices are much more reliable than prices for buying land where renting land is very common, as in Germany, this author does not report marginal effects of climate and therefore, this study is not included in Table 2.2.[31] However, Table 2.2

[29] This is true if rents are wholly paid at the beginning of the agricultural cycle.

[30] Palmquist (1989) states that land rental prices depend on the characteristics of the land and the interaction between demanders and suppliers determine the equilibrium prices in a particular market. On the demand side, farmers maximise expected profits at the beginning of the agricultural year subject to a farm's production function, which depends on prices of outputs and inputs, a vector of lands' characteristics and farmers' skills, and determine their willingness to pay for a particular parcel. In equilibrium, a marginal increase in the willingness to pay for a marginal change in one attribute of land is equal to the marginal increase of the rental price in the market for the marginal change in the corresponding attribute. Regarding the supply side, landowners maximise profits by altering those characteristics of the land under their control, e.g. irrigation and other facilities. In equilibrium, landowners maximise profits by equating the marginal price of a particular attribute with marginal prices in the market. Under such circumstances, the derivative of the hedonic rental price equation with respect to a particular attribute is equal to the implicit price of that characteristic.

[31] Overall, there are few studies (2) using rental prices to identify the effect of climate change on agriculture through the Ricardian hedonic regression. This perhaps occurs because renting land is not very common, especially in developing countries where land markets may not operate properly.

shows marginal effects of climate variables on rental prices in Lippert et al. (2009), who to the best of our knowledge is the only article reporting marginal values of climate resulting from a rental price equation. In average, Lippert et al encounter that one additional degree Celsius increases current rental prices by approximately 15% with respect to the sample mean in Germany. The effect of rainfall on rental prices differs from one location to another. Lands in East Germany will benefit from an additional mm. of rainfall (0.13 €/ha/mm. or 0.07%/mm. of the average rental price). On the other hand, Lippert et al. (2009) predicts harmful effects of additional rainfall for those lands in West Germany (0.40 €/ha/mm. or 0.22%/mm. of the average rental price).

**Table 2.2 Land rental prices and implicit prices of climate (marginal effects)**

| Source | Place | Period | Units of analysis | Functional form | Dependent variable | Climate and margins (implicit prices)+++ |
|---|---|---|---|---|---|---|
| Lippert et al. (2009) | Germany | 1999 | 439 districts | Spatial error model | Rental price per hectare (mean=€183) | Change in rental prices (€/ha)<br>Rain. spring (1 mm): -0.40***<br>Rain. spring*East (1 mm): 0.53**<br>Temperature (1 ºC): 27.74*** |

***, ** and * statistically significant at 1%, 5% and 10% significance level respectively
+ test for significance not reported, ++ bold numbers indicate that the marginal effect is significant at the 10%
+++Marginal effects evaluated at means.

The empirical analysis in Lippert et al. (2009) uses district-level data. By aggregating the data, the Ricardian model is unable to capture farm-level characteristics, heterogeneity among farms, and some relationships between climate variables. Fezzi and Bateman (2015) show that interactions between climate variables, e.g. temperature and rainfall, disappear (statistically insignificant) when farm-level data is not available and researchers use aggregated data. Using panel data, Fezzi and Bateman (2015) encounter that more rain acts as a mitigating factor for increased heat stress, which is consistent with literature on agronomy. Such effect disappears when the authors aggregate farm-level data to the Nomenclature of Territorial Units for

Statistics (NUTS) in the European Union.[32] Moreover, Fezzi and Bateman (2015) show that predictions based on aggregated data, as in Lippert et al. (2009), may lead to biased results and the reader should interpret them accordingly.

Aside from Fezzi and Bateman's arguments about data aggregation in section 2.2.2, Timmins (2006) argues that the lack of farm-level data and using aggregated data instead may lead to endogeneity issues. According to Timmins (2006), some land attributes of particular plots or farmers' characteristics within a certain area are not observable due to data aggregation; therefore, these characteristics are part of the error term. Endogeneity arises because such factors may depend on climate variables in the Ricardian hedonic model. For instance, biases in the parameter estimates arise because aggregated data ignores that farmers allocate heterogeneous parcels to alternative uses within the same unit of analysis (district, municipality or county) and this allocation is sensitive to climatic factors. Timmins argues that if farm-level data is available, this issue is not likely to arise. It is important to highlight that issues related to data aggregation apply not merely to rented land but also to other sorts of measures of land rents.

#### *2.2.2.3. Net revenues*

Most of the empirical work in developing countries uses net revenues in the Ricardian model due to the lack of reliable measures of land rents and distortions in land markets (Timmins, 2006; Maddison et al., 2007; Fleischer et al., 2008; Wang et al., 2014). Mendelsohn et al. (1994) argue that, under perfect competition, land rents are equal to net revenues[33] if landholders allocate their fields to the 'optimal' use.[34] Mendelsohn (2014) define the optimal use of land as

[32] NUTS are roughly equivalent to GB counties.
[33] Value of total output minus value of non-land inputs. This definition of net revenues is similar to the concept of 'variable profits' in Palmquist (1989).
[34] This assumption is widely used in the literature on Ricardian Hedonic models looking at the effect of climate change on agriculture using net revenues. However, it is likely that farmers in developing countries do not have enough market information

the use that gives landholders the highest net revenue. For instance, wheat is the most suitable crop for a particular plot of land but, global warming may prevent its cultivation and the farmer should allocate that land to a more suitable crop, e.g. corn, in order to maximise net revenues. In this regard, the Ricardian approach assumes full farmers' adaptation to current climate conditions.[35]

The main advantage of using net revenues is that data on annual revenues and expenses is usually available in developing countries. However, the quality of such data may distort parameter estimates in the Ricardian model. Mendelsohn et al. (1994) define net revenues as the difference between total revenue and non-land costs. Thus, the residual measures the cost of land or land rent. To compute net revenues, researchers should have access to detailed information on costs, especially on the cost of capital; otherwise, net revenues may suffer from measurement errors. Another disadvantage is that net revenues are observable at the end of the agricultural year (or season), and therefore, are sensitive to unexpected events. In such cases, the difference between revenues and non-land costs may not be equivalent to land rents or land rental prices. Having all the aforementioned deficiencies in mind, previous studies assume that changes on climate will be capitalised in net revenues.

Table 2.3 summarises previous findings from studies using net revenues in the Ricardian hedonic model.[36] Interestingly, we observe an enormous variation in implicit prices of temperature and rainfall among countries.[37] Sometimes, implicit prices of climate variables exceed the average net revenue per unit of land. For instance, Eid et al. (2007) argue that an additional degree Celsius in winter (summer) temperature increases (reduces) net revenues by

to allocate their lands to their optimal uses. If this assumption does not hold, net revenues do not measure land rents accurately. In this regard, Timmins (2006) makes an effort to determine the optimal use of land through a set of simulations for the Brazilian agriculture sector.

[35] For further details, refer to Mendelsohn et al. (1994) p. 754.

[36] These are only studies that report marginal effects of climate variables.

[37] This variation might be explained by the use of different baseline temperature and rainfall values.

363% (-610%). Similarly, other authors encounter marginal effects that exceed the average value of net revenues (Jain, 2007; Deressa and Hassan, 2009; Gebreegziabher et al., 2013). We do not observe these large effects in the land values and rental price Ricardian hedonic models (see Tables 2.1 and 2.2).

Net revenue equations might overestimate the size of implicit prices of climate because these models may suffer from omitted variables and measurement errors. Some authors struggle with the computation of net revenues, especially when there is not enough data on the cost of capital, e.g. machinery, equipment, and buildings; family labour; and the use of animal power in production activities (see for example Eid et al. (2007), Molua and Lambi (2007), Jain (2007), Deressa (2007) and Mano and Nhemachena (2007)). We deal with such difficulties in detail in the following section when we examine the data on Mexican farms.

Galindo et al. (2015) assess the impact of climate change on agriculture in Mexico using net revenues per unit of land. This study uses a panel of 2,431 municipalities from 2003 to 2009 to estimate a Ricardian hedonic model. These authors compute net revenues as the difference between gross revenue[38] and non-land costs[39] per municipality. The socio-economic data comes from the State and Municipality Data System (SIMBAD) and the Agri-food and Fisheries Information Service (SIAP). Climate data comes from the SMN and comprises long-term averages of temperature and rainfall for a 2.5*2.5-miles-grid. The parsimonious model comprises the linear and square terms of seasonal temperature and rainfall, diurnal temperature, subsidies, mechanised lands, water supply, piped water supply, electricity, cropland, cropland square, altitude, latitude, educational services, number of schools, income's inequality, population density, municipal, and year dummy variables.

[38] The value of all agriculture commodities.
[39] Cost of transport, packaging, marketing, storage, post-harvest losses, hired labour, light farms' tools, rental or costs of heavy machinery, value of buildings, fertilisers, pesticides and the annual cost of capital.

## Table 2.3 Net revenues and implicit prices of temperature and rainfall

| Source | Place | Period | Units | Functional form | Dep. Variable | Climate and margins (implicit prices)[+++] |
|---|---|---|---|---|---|---|
| Kabubo and Karanja (2007) | Kenya | 2004 | 724 farms (crops) | Linear-linear | Net revenue per ha (mean=$345) | Change in net revenue ($USD/ha)<br>Temp. summer (1 ºC): -59.35<br>Temp. winter (1 ºC): 58.35<br>Temp. overall (1 ºC): -1.35<br>Rain. autumn (1 mm): 8.75***<br>Rain. summer (1 mm): 4.59<br>Rain. overall (1 mm): 13.34*** |
| Eid et al. (2007) | Egypt | 2002 | 549 farms (crops and livestock | Linear-linear | Net revenue per ha (mean=$1,074) | Change in net revenue ($USD/ha)<br>Temp. winter (1 ºC): 3,902.98***<br>Temp. spring (1 ºC): -896.67<br>Temp. summer (1 ºC): -6,547.89***<br>Temp. autumn (1 ºC): 1,704.41<br>Temp. annual (1 ºC): -1,837.17 |
| Molua and Lambi (2007) | Cameroon | 2005 | 719 farms (crops) | Linear-linear | Net revenue per ha | Change in net revenue ($USD/ha)<br>Temp. annual (1 ºC): -15.4**<br>Rain. annual (1 mm): 5.65*** |
| Jain (2007) | Zambia | 2002 | 955 farms (crops) | Linear-linear | Net revenue per ha (mean=$133) | Change in net revenue ($USD/ha) [+]<br>Temp. Nov-Dec (1ºC): -322.62 (-243% of average net revenue)<br>Temp. Jan-Feb (1ºC): 315.70 (237 % of average net revenue) |
| Mano and Nhemachena (2007) | Zimbabwe | 2004 | 500 farms (crops and livestock) | Linear-linear | Net revenue per ha (mean=$356) | Change in net revenue ($USD/ha)<br>Temp. summer (1ºC): -86.34***<br>Temp. autumn (1ºC): 39.05**<br>Temp. winter (1ºC): 34.08***<br>Temp. spring (1ºC): -44.13*<br>Rain. summer (1 mm): 39.54***<br>Rain. autumn (1 mm): 30.90***<br>Rain. winter (1 mm): 23.07*<br>Rain. spring (1 mm): 37.80 |
| Wang et al. (2009) | China | 2001 | 8,405 farms (crops) | Linear-linear | Net revenue per ha (mean=¥10,146) | Change in net revenue (¥ Yuan/ha)<br>Temp. summer: 76**<br>Temp. autumn: -29<br>Temp. winter: 173***<br>Temp. spring: -230**<br>Rain. summer: -2<br>Rain. autumn: -1<br>Rain. winter: 36***<br>Rain. spring: -19** |
| Deressa and Hassan (2009) | Ethiopia | 2004 | 550 farms (crops) | Linear-linear | Net revenue per ha (mean=$1,214) | Change in net revenue ($USD/ha)<br>Temp. winter (1ºC): -997.85***<br>Temp. spring (1ºC): 375.83<br>Temp. summer (1ºC): -1,277.28**<br>Temp. autumn (1ºC): 1,877.69***<br>Rain. winter (1 mm): -464.76***<br>Rain. spring (1 mm): 225.08***<br>Rain. summer (1 mm): -18.88<br>Rain. autumn (1 mm): -64.19 |
| Gebreegziabher et al. (2013) | Ethiopia | 2005 | 880 farms (crops and livestock) | Linear-linear | Net revenue per ha/per farm (mean crops/livestock= 2,870 birr/651 birr) | Change in net revenue (Birr/ha)<br>Temp. summer (1ºC): 3,166.97<br>Temp. winter (1ºC): -273.37***<br>Temp. spring (1ºC): 2,455.61**<br>Temp. autumn (1ºC): -6,043.36***<br>Rain. summer (1mm): 55.20***<br>Rain. winter (1mm): 83.20<br>Rain. spring (1mm): 7.40<br>Temp. autumn (1mm): -57.05*** |
| Wang et al. (2014) | China (North and South) | 2001 | 8,405 farms (crops) | Linear-linear | Net revenue per ha (mean= ¥10,146) | Change in net revenue (¥ Yuan/ha) [+]<br>Temp. spring (1ºC): -184 (N) and -431 (S)<br>Temp. summer (1ºC): 0 (N) and 681 (S)<br>Temp. autumn (1ºC): -188 (N) and -1,257 (S)<br>Temp. winter (1ºC): 0 (N) and 461 (S)<br>Rain. spring (1mm): 66 (N) and -27 (S)<br>Rain. summer (1mm): -13 (N) and 9 (S)<br>Rain. autumn (1mm): -48 (N) and 0 (S)<br>Rain. winter (1mm): 32 (N) and 76 (S) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Seo et al. (2009) | Africa | 2003 | 8,509 farms (crops and livestock) | Linear-linear | Net revenue per ha (mean=$392-$8,247) | Change in net revenue ($USD/ha) [+]<br>Temperature (1 ºC): -23.96 [-34.17- -7.58]<br>Rainfall (1 mm/mo): -0.89 [-3.95- 3.93] |
| Kurukulasuriya et al. (2006) | Africa | 2003 | 9,064 farms (crops and livestock) | Linear-linear | Net revenue per ha/farm (mean=see article) | Change in net revenue ($USD/ha/farm)<br>Temp. dryland crop (ha-1ºC): -10<br>Temp. irrigated crop (ha-1ºC): 72***<br>Temp. livestock (farm-1ºC): -293<br>Rainfall dryland crop (ha-1mm): 1.50***<br>Rainfall irrigated crop (ha-1mm): -0.90<br>Rainfall livestock (farm-1mm): -5.20 |
| Galindo et al. (2015) | Mexico | 2003-2009 | 2,431 municipalities | Log-linear | Net revenue per ha (mean irrigated/rainfed/mixed= $31,698/$6,790/$14,172 | Change in net revenue ($MXN/ha) [++]<br>Temp. winter (1ºC): **2,049**/**500**/53<br>Temp. spring (1ºC): **-4,818/-984/35**<br>Temp. summer (1ºC): -5,861/**1,270/-1,160**<br>Temp. autumn (1ºC): **2,247/-1,410/-1,202**<br>Rain. winter (1mm/mo): 6/**-40/-298**<br>Rain. spring (1mm/mo): **-939/-0.38**/-200<br>Rain. summer (1mm/mo): **-20**/**0.10**/-3<br>Rain. autumn (1mm/mo): -70/**-0.11**/51.91 |
| Seo and Mendelsohn (2008a) | Africa | 2003 | 8,526 farms (crops and livestock) | Linear-linear | Net revenue per ha | Change in net revenue ($USD/ha) [+]<br>Temperature (1 ºC): -35.15-36.15<br>Rainfall (mm/mo): -108.74-26.87 |
| Seo and Mendelsohn (2008b) | Africa | 2003 | 3,881 farms (livestock) | Linear-linear | Net revenue per head (mean=$1.55-$221) | Change in net revenue ($USD/head) [+]<br>Temperature (1 ºC): -5.57-11.07<br>Rainfall (1 mm/mo): -0.72-0.08 |
| Mendelsohn and Nordhaus (1992) | Unites States | 1982 | 2,939 counties (crops) | Linear-linear | Gross revenue per acre | Change in gross revenue ($USD/acre)<br>Temp. January (1 ºF): -10***<br>Temp. April (1 ºF): -15***<br>Temp. July (1 ºF): -23***<br>Temp. October (1 ºF): 41***<br>Rain. January (1 inch): 24***<br>Rain. April (1 inch): -24***<br>Rain. July (1 inch): 8**<br>Rain. October (1 inch): -36*** |
| Mendelsohn et al. (2001) | India | 1966-1986 | 271 districts | Log-linear | Net revenue per hectare | Change in net revenue ($USD/ha)[+]<br>Temperature (1966-1975/1ºC): -242.7<br>Temperature (1977-1986/1ºC): -36.4<br>Rainfall (1966-1975/1mm): -60.3<br>Rainfall (1977-1986/1mm): 51.7 |
| Seo et al. (2005) | Sri Lanka | 1995 | 25 districts | Linear-linear | Net revenue per hectare | Change in net revenue ($USD/ha)<br>Temperature (1ºC): -49.9<br>Rainfall (1mm): 0.7 |
| Abidoye et al. (2017) | South-East Asia | 2013-2014 | 1,429 farms (crops) | Linear-linear | Net revenue per hectare | Change in net revenue ($USD/ha)<br>Temp. spring (1ºC): -11<br>Temp. summer (1ºC): -1,203**<br>Temp. autumn (1ºC): 894***<br>Temp. winter (1ºC): 222<br>Rain. spring (1 mm): 4.15<br>Rain. summer (1 mm): 4.64**<br>Rain. autumn (1 mm): -26.54***<br>Rain. winter (1 mm): 21.57*** |
| Batsuuri and Wang (2017) | Mongolia | 2013 | 301 farms (livestock) | Linear-linear | Net revenue per head | Change in net revenue ($USD/ha)<br>Temperature (1 ºC): -1.473***<br>Rainfall (1 mm): -1.068*** |

***, ** and * statistically significant at 1%, 5% and 10% significance level respectively
[+] test for significance not reported, [++] bold numbers indicate that the marginal effect is significant at the 10%

The main results in Galindo et al. (2015) suggest that in the event of a warmer and drier future, net revenues would decrease in Mexico, especially in irrigated fields. Using a uniform-climate change scenario in which temperature rises 2.5ºC and the volume of rainfall diminishes by 10% with respect to current levels, these authors predict losses from 19% to 36% of the current net revenues. Galindo et al. (2015) also estimate a Ricardian hedonic model for each year in the sample. Looking at annual marginal effects of temperature, one additional degree Celsius would reduce net revenues between -$9,600 (-26% of average net revenue) and -$3,072 (-9%), -$618 (-10%) and -$126 (-2%), and from -$3,838 (-30%) to -$954 (-9%) in irrigated, rain-fed, and mixed lands respectively. Regarding annual marginal effects of rainfall, one extra mm. of rain in the same groups of farms would change net revenues between -$2,457 (-8%) and $918 (3%); from -$350 (-5%) to -$72 (-1%); and from -$605 (-4%) to $522 (4%) respectively.

Implicit prices of temperature and rainfall in Galindo et al. (2015) are rather high in some cases. This may be due to the omission of soil characteristics, which are not accounted for in the hedonic regression. Aside from the omission of soil features, the enormous variation of net revenues within the sample may also lead to overstate implicit prices of climate (Jain, 2007; Eid et al., 2007; Deressa and Hassan, 2009). Furthermore, aggregating the data at the municipality level hides farms heterogeneity, which is important for predictions about likely effects of climate change in agriculture. In fact, Galindo et al. (2015) assume additively separable effects of temperature and rainfall and do not include the interaction term in the hedonic regression as pointed out by Fezzi and Bateman (2015).

Data aggregation in Galindo et al. (2015) may also lead to endogeneity issues because unobservable determinants of land values are part of the error term, e.g. different land uses, which may depend on climate variables in the Ricardian equation. Timmins (2006) argues that ignoring that heterogeneous plots are allocated to alternative uses leads to misspecification of implicit prices of climate. This would also explain why Galindo et al. (2015) find such high implicit values.[40]

[40] To solve this issue, Timmins (2006) models land use decisions, aggregates such land use decisions to a higher level (land shares at the county or district level), and investigates the determinants of land values per unit of land by use.

### *2.2.3. Additional methodological issues*

Apart from the abovementioned issues, we identify some factors that should be taken into account when researchers estimate a Ricardian Hedonic model. Darwin (1999) points out that Mendelsohn et al. (1994) omit irrigation in the hedonic model and argue that such omission leads to biased estimations. In this regard, Darwin (1999) proposes to include the share of irrigated land per county or region in the hedonic regression. Moreover, Darwin argues that Mendelsohn et al violate the economic principle that land rents are strictly positive and net revenues may not satisfy this condition. Here, Darwin (1999) suggests including those counties (areas) with no farmland (value of farmland equals zero) and estimating a Tobit model.

After Darwin's criticism, Mendelsohn and Nordhaus (1999) and Mendelsohn and Dinar (2003) address the shortcoming pointed out by Darwin about the omission of irrigation by analysing water availability in the Ricardian hedonic model. In line with this, Maddison et al. (2007) argue that accounting for water runoff improves parameter estimates of the hedonic model. In recent years, this strand of literature proposes two different ways to deal with irrigation in the hedonic model. First, researchers should estimate separate regressions for irrigated and rain-fed farms. Second, researchers should treat irrigation decisions, e.g. adopting or not adopting irrigation, as an endogenous factor and use a two-stage estimation in the hedonic model.

To examine how alternative land uses (farm types) influence parameter estimates as pointed out by Timmins (2006), Seo and Mendelsohn (2008c) split the sample and estimate a Ricardian hedonic model for each farm type in South America.[41] The main purpose of such investigation is to test whether farmers endogenously choose farm types or not. By looking at parameter estimates from the abovementioned subsamples, Seo and Mendelsohn (2008c) hint that

[41] Crop only, livestock only and mixed farms.

endogenous switching between farm types has an effect on the Ricardian model estimations. Rather than splitting the sample into different farm types, Mendelsohn and Dinar (2009) propose a two-stage procedure that accounts for endogenous switching among farm types, the so-called structural Ricardian model. This approach explicitly models farmers' adaptation by using a Multinomial Logit model for crop choices in the first stage, and then, it uses the corresponding choice terms in the second stage (or the Ricardian hedonic model). One of the main criticisms to the structural Ricardian model is that it assumes no barriers or zero transition costs from one agricultural activity to another (Runge, 2010).

Patton and McErlean (2003) introduce spatial effects in the Ricardian hedonic model. This specification accounts for spatial heterogeneity (variation across space) and spatial correlation (correlation between observations across space). These scholars argue that ignoring spatial effects may lead to biased estimations in the Ricardian model. Using data from Northern Ireland, Patton and McErlean (2003) encounter that average local prices of land per acre also have an effect on farmland prices. Maddison (2009) explores the spatio-temporal lag specification using data on 507 public auctions (sales) in England and Wales and encounters that the spatio-temporal lagged value of both dependent (land prices) and explanatory variables (land's attributes) significantly contribute to explain the variation of farmland prices.[42]

Most of the Ricardian hedonic models use cross-sectional data to identify the effect of climate on land rents by looking at variations of the land rents-climate relationship across space rather than across time, e.g. panel data. In this regard, Deschenes and Greenstone (2007) argue that the hedonic approach may confound climate with other variables and propose a 'new' framework. It explores the random year-to-year variation of weather and identifies the effect of such variation on agricultural profits. In contrast with the Ricardian hedonic approach,

[42] For further details about spatial models, see Anselin (2010).

Deschenes and Greenstone argue that extreme events are unlikely to influence parameter estimates of the year-to-year profits model and conclude that the hedonic technique is extremely sensitive to the selection of control variables, samples, and weights.

Fisher et al. (2012) contribute to this debate by replicating the empirical exercise in Deschenes and Greenstone (2007). Fisher et al. (2012) encounter some errors in Deschenes and Greenstone (2007). First, there are errors in weather data and climate change projections. Second, the omission of spatial correlation leads to biased estimates of standard errors. Third, the inclusion of year fixed effects influence the initial estimates. Fourth, using storage and inventory adjustments invalidates the use of annual profits. Thus, Fisher et al. (2012) conclude that if the specification of the hedonic model is correct, the parameter estimates are consistent and robust.[43] In this regard, Massetti and Mendelsohn (2011) propose a panel data specification for the Ricardian hedonic model. Using county-level data from the US, Massetti and Mendelsohn state that repeated cross-sectional estimations are not stable over time while panel data models provide stable outcomes.

## 2.3. Method and materials

### *2.3.1. Theory*

To describe the rationale behind the Ricardian hedonic model, let us assume that relevant information is observable either at the beginning of $(t_0)$ or at the end of $(t_1)$ the agricultural year. In $t_0$, the farmer $(i)$ maximises expected net revenues[44] by choosing optimal quantities of inputs and looking at factors out of his control, e.g. climate, then the farmer elaborates production plans accordingly. The farmer determines his willingness to pay (WTP) for a plot

[43] See Deschenes and Greenstone (2012) for their reply to Fisher and colleagues' article.
[44] Here, we define net revenues as the difference between total revenues and non-land expenses. This definition coincides with 'variable profits' in Palmquist (1989) and Mendelsohn et al. (1994).

of land looking at structural land attributes that meet his optimal production plans. Rental prices result from a two-sided optimisation mechanism in the land market in which each landowner offers a parcel with specific attributes, if those features meet farmer's requirements (demand) then, in $t_0$, landowners and farmers reach an agreement about the rental price. In $t_1$, the farmer observes actual values of output, prices, and annual weather therefore, each farmer is able to see whether actual net revenues are in line with his original expectations at $t_0$.

On the demand side, Palmquist (1989) defines the optimisation problem at $t_0$ as follows:

$$\max_{q,x} \pi = \left(\sum_{m=1}^{M} p_m * q_m\right) - \left(\sum_{j=1}^{J} c_j * x_j\right), \text{ subject to } g\left(q_m, x_j, z_l, \alpha\right) = 0 \quad (2.1)$$

where $\pi$ is the net revenue, $p_m$ is the $m$-th price of output $q_m$, $c_j$ is the unit cost of non-land inputs $x_j$, $g(.)$ is the multiple-output and multiple-input production function, $z_l$ is a vector of characteristics of the land and $\alpha$ is a vector of farmer's characteristics that influence the production process. Solving for the corresponding outputs ($q_m$) and non-land input demands ($x_j$), we obtain $q_m^* = q_m^*(p_m, z_l, \alpha)$ and $x_j^* = x_j^*\left(c_j, z_l, \alpha\right)$. By replacing outputs and inputs with their optimal values, $q_m^*$ and $x_j^*$, in equation (2.1), we obtain the optimal net revenue:

$$\pi^* = \pi^*\left(p_m, c_j, z_l, \alpha\right) = \sum_{m=1}^{M} p_m * q_m^*(p_m, z_l, \alpha) - \sum_{j=1}^{J} c_j * x_j^*\left(c_j, z_l, \alpha\right) \quad (2.2)$$

Taking the difference between optimal expected net revenues ($\pi^*$) and the cost of land, we obtain the desired profit ($\pi^D$). Therefore, the farmer's WTP (bid) for a particular plot of land is equal to:

$$WTP\left(p_m, c_j, z_l, \alpha, \pi^D\right) = \pi^*\left(p_m, c_j, z_l, \alpha\right) - \pi^D \quad (2.3)$$

According to Palmquist (1989), the characteristics of the land ($z_l$) enter in the production function as fixed factors. If such attributes are desirable then, $\frac{\partial\, WTP}{\partial\, z_l} = \frac{\partial\, \pi^*}{\partial\, z_l} \geq 0$. Applying the envelope theorem, we know that $\frac{\partial\, WTP}{\partial\, p_m} > 0$, $\frac{\partial\, WTP}{\partial\, c_j} < 0$ and $\frac{\partial\, WTP}{\partial\, \pi^D} = -1$. In equilibrium, the marginal increase in rental price of land is equal to the marginal increase in farmer's WTP when there is a marginal change in any of the land attributes. Furthermore, total WTP must be equal to the rental price of the plot in the market.

On the supply side, landowners can modify some of the attributes of land. So, we can split $z_l$ into two sub-vectors, $\check{z}_l$ and $\tilde{z}_l$, where $\check{z}_l$ are exogenous features such as climate and $\tilde{z}_l$ are characteristics under his control such as irrigation facilities. Palmquist (1989) states that landowners choose the levels of $\tilde{z}_l$ to maximise profits as follows:

$$\max_{\tilde{z}_l} \pi^s = R(\check{z}_l, \tilde{z}_l) - C(\check{z}_l, \tilde{z}_l, c_c, \beta)\, , \text{subject to } \pi^s \geq 0 \tag{2.4}$$

where $\pi^s$ are profits, $R(.)$ is the land rental price, $C(.)$ is a cost function, $c_c$ stands for the unit cost of the $c$-th input, and $\beta$ represents technical characteristics of landowners. First-order conditions indicate that the marginal cost of attribute $\tilde{z}_l$ equals its marginal price in the market $\left(\frac{\partial\, R(\check{z}_l,\tilde{z}_l)}{\partial\, \tilde{z}_l} = \frac{\partial\, C(\check{z}_l,\tilde{z}_l,c_c,\beta)}{\partial\, \tilde{z}_l}\right)$. To obtain the offer function ($\phi(.)$), we solve for the optimal value of $\tilde{z}_l$ and plug the corresponding optimal values in equation (2.4):

$$\phi(\check{z}_l, \tilde{z}_l^*, c_c, \beta, \pi^{s*}) = \pi^{s*} + C(\check{z}_l, \tilde{z}_l^*, c_c, \beta) \tag{2.5}$$

where $\pi^{s*}$ is the optimal (desired) profit. From (2.5), we know that $\frac{\partial\, \phi}{\partial\, \tilde{z}_l^*} = \frac{\partial\, C}{\partial\, \tilde{z}_l^*} > 0$ and $\frac{\partial\, \phi}{\partial\, \pi^{s*}} = 1$. Regarding land attributes out of landowners' control, demand in the market completely determines the price of $\check{z}_l$ and owners of the land adjust their offer prices accordingly. For instance, if the bid were greater than the offer price, the landowner would forego revenues; or, if the offer were greater than the bid price, the farmer would not take the plot. Under such circumstances, the price of climate attributes, which are attached to land, are demand-determined.

The interaction between farmers (tenants) and landowners at $t_0$ determines land market rental prices, which are equal to $WTP(p_m, c_j, z_l, \alpha, \pi^D) = \phi(\check{z}_l, \tilde{z}_l^*, c_c, \beta, \pi^{S*})$ in equilibrium. Previous studies using net revenues in the Ricardian hedonic model assume perfect competition between farms (Mendelsohn et al., 1994). This assumption implies that $WTP(p_m, c_j, z_l, \alpha) = \pi^*(p_m, c_j, z_l, \alpha)$ in equation (2.3) since $\pi^D = 0$. Thus, in equilibrium rental prices ($R$) equal the farmers' bid ($WTP$) and net revenues ($\pi^*$). However, if $\pi^D \neq 0$, then $WTP(p_m, c_j, z_l, \alpha) \neq \pi^*(p_m, c_j, z_l, \alpha)$, which may lead to biased results in the Ricardian hedonic model. For instance, if $\pi^D$ is considerably large,[45] we overestimate the WTP for a specific parcel by assuming $\pi^D = 0$ therefore, we may also overestimate implicit prices of attributes of the land, e.g. climate.

Farmers observe actual net revenues ($\pi^a$) at $t_1$ and may not be in line with their original expectations ($\pi^*$). Previous studies assume that $WTP(p_m, c_j, z_l, \alpha) = \pi^a(\check{p}_m, \check{c}_j, \check{z}_l, \alpha)$ because $\pi^a = \pi^*$. Nonetheless, unexpected events within the agricultural year ($t_0$-$t_1$) deviate prices and levels of land attributes from their expected values. For example, if annual weather deviates from long-term climate in the current year, $z_{climate} - \check{z}_{weather} \neq 0$, then $WTP(p_m, c_j, z_l, \alpha) \neq \pi^a(\check{p}_m, \check{c}_j, \check{z}_l, \alpha)$. Thus, if any of the arguments in the $WTP$ and the $\pi^a$ equations deviate from their expected values ($p_m \neq \check{p}_m, c_j \neq \check{c}_j$ or $z_l \neq \check{z}_l$), the WTP (rental price) for an specific parcel at the beginning of the agricultural year will not coincide with net revenues at the end of the agricultural year.

### *2.3.2. Ricardian hedonic model*

The Ricardian hedonic model regresses farmland prices, net revenues, or rental prices per unit of land on attributes of the land. The key assumption of this approach is that farmers are fully

[45] Large positive profits, otherwise farmers should abandon the market.

adapted to current climate conditions therefore, variations in climate across space, which is attached to lands, partially explains the variation of land prices. Thus, the Ricardian hedonic model is able to predict the capitalisation of climate in land prices using cross-sectional data. According to Mendelsohn and Dinar (2009) and the profit maximisation behaviour described in section 2.3.1, the reduced form of the Ricardian hedonic model is as follows:

$$V = V(F, S, H) = \beta_0 + \beta_1 F + \beta_2 F^2 + \beta_3 S + \beta_4 H + u \tag{2.6}$$

where land value per hectare is equal to $V = \int \pi^* \, e^{-\varphi t} dt$, $e^{-\varphi t}$ is the discount factor of future net revenues or land rents, $F$ is a vector of climate variables,[46] $S$ is a vector of the characteristics of the land[47], $H$ comprises additional control variables[48] and $u$ is the error term. The quadratic terms of climate variables enter in the hedonic model to identify non-linear effects of climate on land values.

Using laboratory experiments, agronomist encounter a non-linear effect of climate variables on crops' yields (see for example Keating et al. (2003)). There is a consensus in this strand of literature, which indicates that temperature shows a hill-shaped relationship with land values. Conversely, there is no agreement on the non-linear relationship between rainfall and land values. The inclusion of square terms of climate in the hedonic model implies that the marginal value (implicit price) of the land attribute depends on its own level:

$$\frac{\partial V}{\partial F} = \beta_1 + 2\beta_2 F \tag{2.7}$$

The literature suggests two methods to compute the marginal value. First, we can evaluate equation (2.7) at the sample mean of $F$, which yields $\frac{\partial V}{\partial F} = \beta_1 + 2\beta_2 E[F]$. Second, we can

[46] In Palmquist (1989), climate variables are part of the $\check{z}_l$ vector (exogenous land attributes).
[47] In Palmquist (1989), the characteristics of the soil are in the $\check{z}_l$ vector (exogenous land attributes).
[48] In Palmquist (1989), these additional control variables should include both types of land attributes, $\check{z}_l$ and $\tilde{z}_l^*$, such as distance to the nearest city and irrigation facilities, respectively.

compute observation-specific marginal effects and take the sample average $\sum_{i=1}^{N}\left(\frac{\partial V_i}{\partial F_i}/N\right) = \sum_{i=1}^{N}\left(\frac{(\beta_1+2\beta_2 F_i)}{N}\right)$.[49] Equation (2.7) assumes that a marginal change in one of the climate variables is independent of other climate variables. However, landowners do not sell/rent land attributes separately, e.g. temperature $(F_1)$ and rainfall $(F_2)$ (Palmquist, 1989). Fezzi and Bateman (2015) justify the importance of including interactions between climate variables in the Ricardian model. Taking such interactions into account, the marginal value of each climate variable is as follows:

$$\frac{\partial V}{\partial F} = \beta_{1,1} + 2\beta_{2,1}F_1 + \beta_{2,2}F_1F_2 \tag{2.8}$$

The log-linear specification of the Ricardian hedonic model represents an alternative functional form to identify the relationship between climate and land values. This functional form is as follows:

$$\ln V = \beta_0 + \beta_1 F + \beta_2 F^2 + \beta_3 S + \beta_4 H + u \tag{2.9}$$

Here, the marginal change in land values given a marginal change in climate, including interactions between climate variables, is:

$$\frac{\partial V}{\partial F} = \left[\beta_{1,1} + 2\beta_{2,1}F_1 + \beta_{2,2}F_1F_2\right] * V \tag{2.10}$$

Thus, marginal effects (implicit prices) of land attributes may depend on the current values of such attributes and land values.

As we stated before, reliable measures of farmland values are not typically available in developing countries due to non-proper land market functioning (Timmins, 2006; Maddison et al., 2007; Fleischer et al., 2008; Wang et al., 2014). To overcome this issue and having

[49] Both methods lead to similar results.

drawbacks and advantages of such indicators in section 2.2.2 in mind, we should use rental prices or net revenues instead of land values. Therefore, the Ricardian hedonic models that we estimate in this chapter are as follows:[50]

$$\pi^a = \pi^a(F,S,H) = \beta_0 + \beta_1 F + \beta_2 F^2 + \beta_3 S + \beta_4 H + u \tag{2.11}$$

$$R = R(F,S,H) = \beta_0 + \beta_1 F + \beta_2 F^2 + \beta_3 S + \beta_4 H + u \tag{2.12}$$

Following section 2.3.1, if $\pi^a = R$, parameter estimates from equations (2.11) and (2.12) are identical. However, if actual net revenues differ from their expected values or if there is not perfect competition in agriculture, then $\pi^a \neq R$, and consequently, parameter estimates from (2.11) and (2.12) are no longer the same. In the following section, we test for significant differences between $\boldsymbol{\beta_{\pi^a}}$ and $\boldsymbol{\beta_R}$.

Using parameter estimates from equations (2.11) and (2.12), we can assess the capitalisation of climate change on land rents as follows:

$$\sum_i \frac{\Delta\pi_i^a}{\Delta F_i} = \sum[\pi^a{}_i(F1_i, S_i, H_i) - \pi^a{}_i(F0_i, S_i, H_i)] * TA_i \tag{2.13}$$

$$\sum_i \frac{\Delta R_i}{\Delta F_i} = \sum[R_i(F1_i, S_i, H_i) - R_i(F0_i, S_i, H_i)] * RA_i \tag{2.14}$$

where $TA_i$ and $RA_i$ are total farmland and rented areas respectively. We compare welfare changes in equations (2.13) and (2.14) in the following section to examine whether these effects are sensitive to the use of either net revenues or rental prices. If so, we also examine the differences between the corresponding assessments.

[50] We also estimate a log-linear Ricardian hedonic model for both indicators of land rents.

### *2.3.3. Data*

This section describes the database that we use to estimate the Ricardian hedonic model. In subsection 2.3.3.1, we explain the construction of both dependent variables: land rental prices and net revenues per unit of land. Regarding subsection 2.3.3.2, since climate data comes from GIS-databases (gridded climate data) and meteorological stations, we explain the allocation of such information to the corresponding farms carefully. Subsection 2.3.3.3 describes the soils' classification released by INEGI (2014b). Subsection 2.3.3.4 contains information about additional control variables in the Ricardian hedonic equations.

#### *2.3.3.1. Rental prices and net revenues*

Farm-level data comes from two waves of the National Agriculture Survey (NAS) in Mexico. The NAS collects information from farms allocating their production efforts to 28 crops[51] and 3 livestock[52] activities in 2012 and 2014. These surveys use representative samples of the entire agriculture sector.[53] The NAS collects data on land costs by asking respondents the following question: *from October 2011 (2014) to September 2012 (2014), how much did you spend on land rents?* As this survey reports land rents at the farm-level, the rental price[54] per hectare is as follows:

$$R_i = \frac{TR_i}{RA_i} \tag{2.15}$$

where $R_i$ is the rental price per hectare in the $i$-th farm, $TR_i$ is total rental payment, and $RA_i$ stands for the total rented land in hectares. To distinguish between rented and non-rented plots

---

[51] Maize, sugar cane, wheat (grain), avocado, sorghum, beans, pepper, alfalfa, tomato (red), potato, melon, watermelon, coffee, oranges, grapes, bananas, lemon, mango, onion, pumpkin, tomato (green), cotton, apples, cocoa, rice, barley, soy, and fodder oat.
[52] Beef cattle, pigs and poultry.
[53] Full samples include data on 85,000 farms and 64,000 farms in 2012 and 2014, respectively.
[54] In Mexico, these prices result from a private negotiation between landowners and tenants (farmers). The government or any other third party are not involved in such agreement.

of land within the same farm, the NAS collects data on property rights of the corresponding fields, e.g. owned, rented, borrowed, etc. Therefore, $RA_i$ may not be equal to total farmland area in some cases.[55]

The survey also contains data on revenues and expenses. Following Palmquist (1989) and Mendelsohn et al. (1994), the net revenue per hectare is as follows:

$$\pi_i = \frac{\left(\sum_{m=1}^{M} p_{mi} * q_{mi}\right) - \left(\sum_{j=1}^{J} c_{ji} * x_{ji}\right)}{TA_i} \quad (2.16)$$

where $p_{mi}$ are prices of the $m$-th outputs ($q_{mi}$) and $c_{ji} * x_{ji}$ are annual expenses on the $m$-th non-land inputs. For total revenue ($\sum_{m=1}^{M} p_{mi} * q_{mi}$), we value self-reported output using farm gate prices[56] of the 31 commodities in the sample. Regarding total non-land costs $\left(\sum_{j=1}^{J} c_{ji} * x_{ji}\right)$, the NAS reports annual expenses on wages, soil tillage, sowing/planting activities, fertilisers, control of plagues, diseases control, weed control, irrigation fees, harvesting activities, balanced feed, medicines, vaccines, surgeries, vet services, rental payments where machinery, equipment and buildings were rented, extension services, gasoline, diesel, oils, electricity, freights, transport, taxes, interests, and other annual payments.

The survey does not report the annual cost of capital for those farms that own equipment and machinery. To measure the annual cost of capital, we calculate the total ownership cost, $TOC_i$, per farm as follows (Edwards, 2011):

$$TOC_i = \sum_{l=1}^{L} (CR_{il} + TIH_{il}) \quad (2.17)$$

$$CR_{il} = (D_{il} * CRF_{li}) + (SV_{il} * r)$$

[55] For now let us assume that the rental price per hectare is the same for all plots in these farms, as if owned plots were rented too. We add separate regressions for farms with 100% rented land in the results section.

[56] Some farmers do not report output prices. This may happen because these farms completely rely on self-consumption. In such cases, we use the national average price of the corresponding commodity.

$$D_{il} = PP_{il} - SV_{il}$$

$$SV_{il} = PP_{il} * RVF_{il}$$

$$TIH_{il} = 0.01 * (PP_{il} + SV_{il})/2$$

where $CR_{il}$ is the capital recovery cost of the $l$-th machinery or equipment, $TIH_{il}$ are taxes, insurances and housing costs, $D_{il}$ is total depreciation, $CRF_{li}$ stands for the capital recovery factor in Edwards (2011), $SV_{il}$ represents the salvage value, $r$ is the real interest rate,[57] $PP_{il}$ is the current list price,[58] and $RVF_{il}$ is the remaining value factor in Edwards (2011).[59] Thus, the total ownership cost per farm comprises the corresponding annual costs of tractors, ploughs, cutters/slicers, harvesters, planters, balers, fumigators, disc harrows, and threshing machines. The NAS also collects data on family labour (working hours) per farm. We value family labour using the minimum wage rate in Mexico.[60] Total non-land costs include annual expenses reported in the NAS, total ownership cost of capital and the cost of family labour. Therefore, net revenue is equal to the ratio of the difference between total revenue and total non-land costs to total (utilised) area ($TA_i$).[61]

#### *2.3.3.2. Climate variables*

The NAS uses digital and printed maps to help respondents to report the location of their fields. For statistical purposes, the National Institute of Statistics and Geography (INEGI by its acronym in Spanish) divides the Mexican territory into 32 states, 2,455 municipalities, 17,422 geo-statistical areas and 295,128 control areas (CA) in order to record the location of

[57] We use an interest rate of 3.25%, which is the 1995-2014 average in Mexico.
[58] We use prices of machinery and equipment released by SAGARPA. The list is available on: http://www.sagarpa.gob.mx/agricultura/Precios/Paginas/PreciosdeMaquinariaAgricola.aspx
[59] Factors available in: https://www.extension.iastate.edu/agdm/crops/html/a3-29.html
[60] We divide the total number of working hours (family labour) by 8 hours to obtain the number of working days per farm per annum. Then, we multiply the number of working days times the minimum wage rate (per day).
[61] We were unable to account for the use of animal power due to data restrictions. The survey only collects data on whether the farm uses oxen or not in agricultural activities but not on the frequency or the number of oxen.

agricultural lands. In the interview, the NAS collects codes for state, municipality, geo-statistical areas, and CAs, which are the key codes for matching net revenues and rental prices to climate variables.

Climate variables include the normal[62] values of temperature, rainfall, days with storms, and cloudy days. Hijmans et al. (2005) interpolate climate variables from meteorological stations for the entire globe using the thin-plate smoothing spline algorithm accounting for latitude, longitude, and altitude of the corresponding stations.[63] Thus, Hijmans et al. (2005) publish 24 GIS-datasets (30 arc-seconds resolution grids, ~1 km$^2$) which include monthly normal values of the 1950-2000 average temperature and rainfall[64] (see Figure 2.4a. for an example of normal values of temperature in June).

To assign normal values to the corresponding plots, we use GIS tools in ArcGis 14.1. First, we create a points-layer using the centroid of each square kilometre in the 24 layers. Second, using the points-layer we extract normal values of temperature and rainfall for the entire territory of Mexico (~1.96 million km$^2$). Third, we intersect the points-layer (with climate data) and the polygons-layer in Figure 2.4b to obtain normal values per control area. Fourth, for CAs larger than 1km$^2$, we take the average of points (normal values) within the corresponding polygon (see Figure 2.4c). For those CAs smaller than or equal to 1km$^2$, we extract normal values of temperature and rainfall using their centroids (see Figure 2.4d).

[62] Long-term average of climate variables, which usually comprises 30-50 years.
[63] Climate data in Hijmans et al. (2005) come from a large number of sources. First, from the Global Historical Climate Network Dataset (GHCN), 20,590 stations report monthly data on rainfall, 7,280 on average temperature, and 4,966 on minimum and maximum temperature. Second, from the WMO climatological normal values (CLINO), 3,084 stations capture monthly average temperature, 2,504 stations maximum and minimum temperature and 4,261 rainfall. Third, FAOCLIM 2.0 contains monthly rainfall data from 27,372 stations, mean temperature from 20,825 locations and minimum and maximum temperature from 11,543 stations. Fourth, the International Centre for Tropical Agriculture (CIAT) provides monthly data on rainfall (18,895 stations), mean temperature (13,842 stations), and minimum and maximum temperature (5,321 stations). Hijmans et al. (2005) conduct a data quality control, deal with uncertainty and provide a very high resolution on the surfaces they create. Therefore, this dataset comprises reliable information.
[64] Climate data layers available on: http://www.worldclim.org/

**Figure 2.4 Temperature and rainfall data**

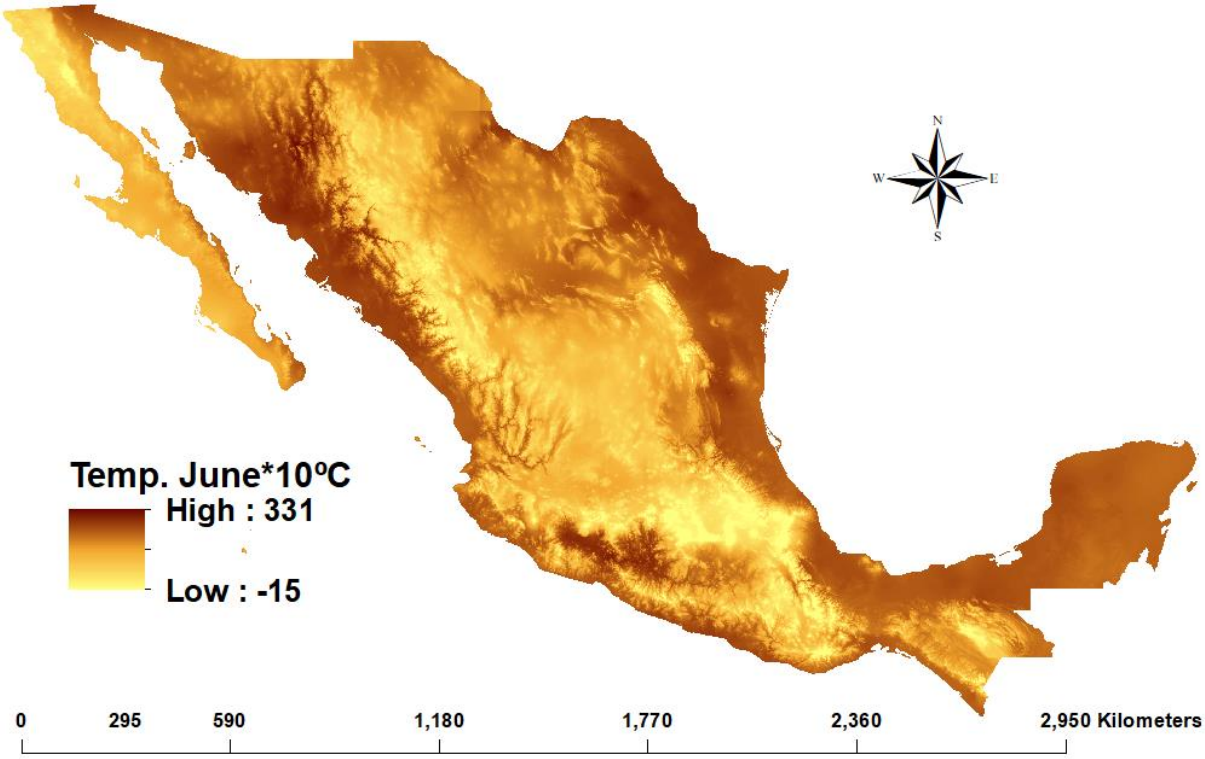



**Figure 2.4a. Temperature ~1km$^2$ (June 1950-2000)**

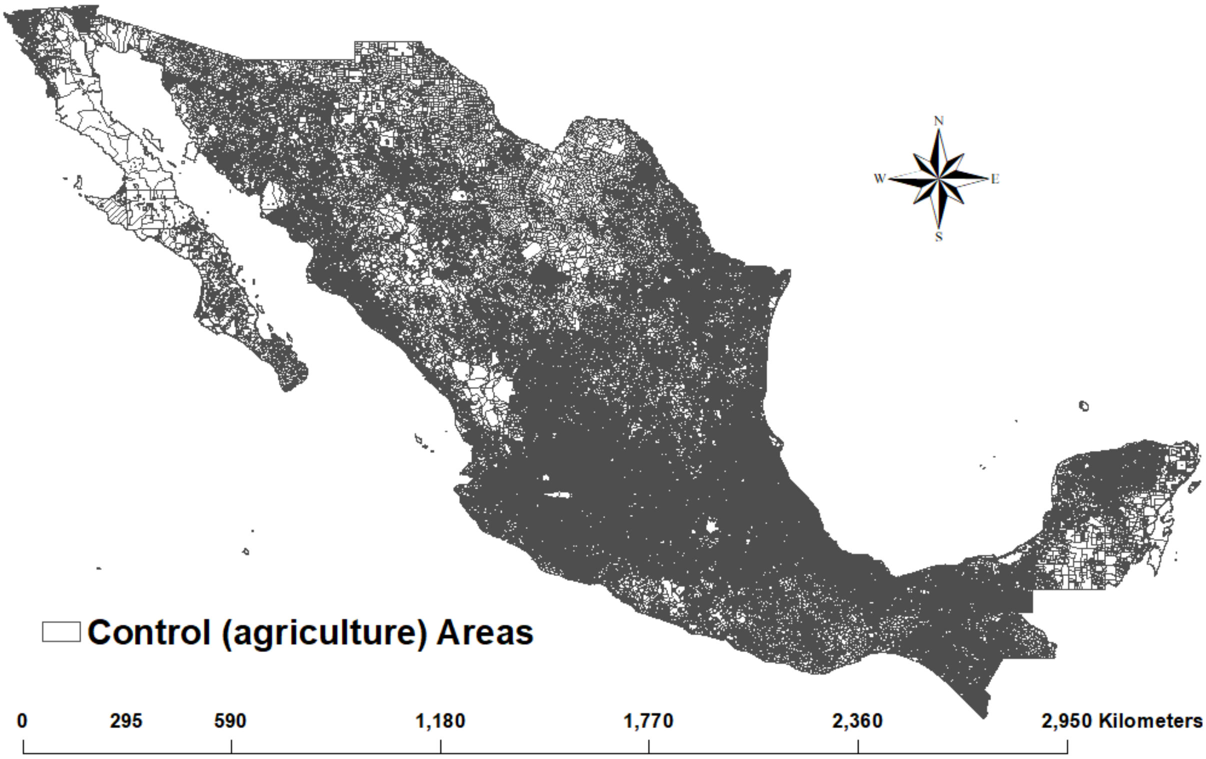



**Figure 2.4b. Control areas**

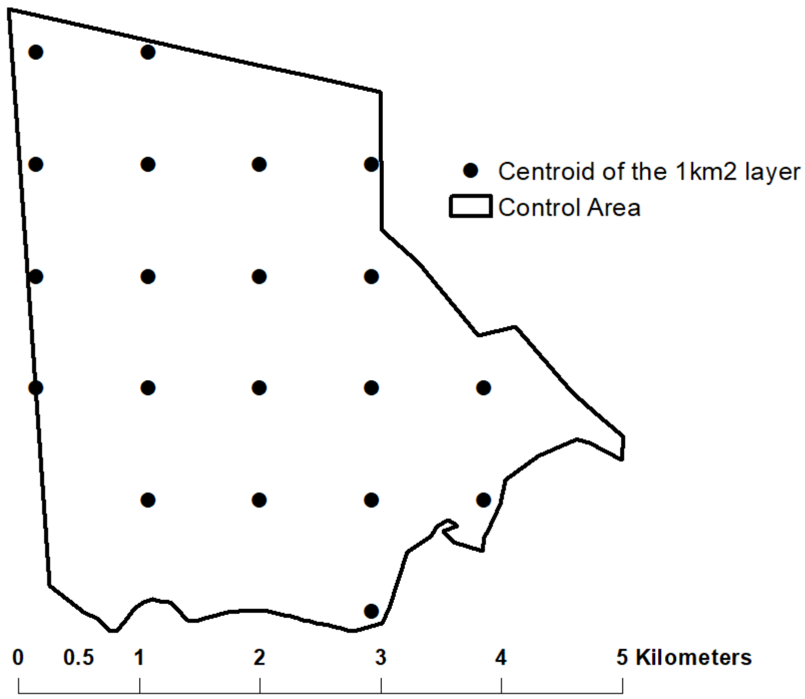



**Figure 2.4c. Control area>1km$^2$**

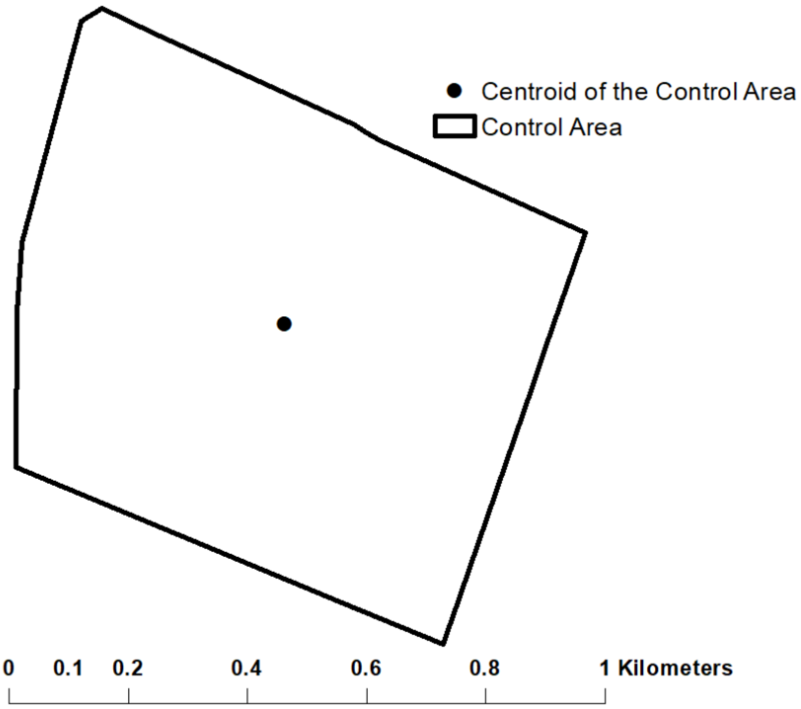



**Figure 2.4d. Control area<=1km$^2$**

Source: own elaboration based on Hijmans et al. (2005)

Rather than using monthly-normal values, we use seasonal climate. Among others, Mendelsohn and Dinar (2009) encounter that monthly values are highly correlated and this correlation may lead to multicollinearity issues. Moreover, the agricultural year in Mexico comprises two crop seasons: spring-summer and autumn-winter. Therefore, we compute the average (total) temperature (rainfall) in the periods of March-August and September-February for the corresponding seasons. Because farmers report rental prices and net revenues at the farm-level and climate data varies among plots within the same farm (plot-level data), we use a weighted average, which is as follows:

$$T_{is} = \sum_{j=1}^{J} \frac{T_{isj} * a_{ij}}{A_i} \tag{2.18}$$

where $T_{is}$ is the average (total) seasonal temperature (or rainfall) in farm $i$, $s$ stands for the corresponding season, $T_{isj}$ is the normal temperature (rainfall) in plot $j$, $a_{ij}$ is the size of the plot, and $A_i$ is total farmland area, which is equal to $RA_i$ or to $TA_i$ in the rental price or net revenue equations respectively. Although 41% and 43% of farms in the 2012 and 2014 samples have one plot respectively, the remaining farms have, in average, three plots, which may be located in different control areas. Due to the extremely fragmented orography in Mexico, climate can be radically different from one control area to another, even among adjacent control areas. Therefore, the use of land-share weights helps us to consider such variation in farms with more than one agricultural field.

The second set of climate variables considers the long-term averages of days with storms, days with hail, and cloudy days in a specific season. The United Nations develops a climatological software operated by the SMN in Mexico, CLImate COMputing project. It reports daily data on storms and clouds from 5,459 meteorological stations (see Figure 2.5a). One can find data on different periods between 1920 and 2016. Therefore, this database is temporarily compatible with Hijmans et al. (2005).

Before we analyse the data, we conduct quality controls over this database. First, we exclude stations with less than 10 years of continuous daily information and those stations operating before 1950, thus, the remaining set comprises 3,388 stations. Second, by taking the average of the total number of storm and cloudy days per season and station, we interpolate these values applying the Thiessen method as the hydrological literature suggest (Thiessen, 1911; Brassel and Reif, 1979; Tabios and Salas, 1985; Hartkamp et al., 1999). This technique creates a polygon for each point (station) containing all the closest areas to it (see Figure 2.5b).

**Figure 2.5 Days with storms and dense clouds**

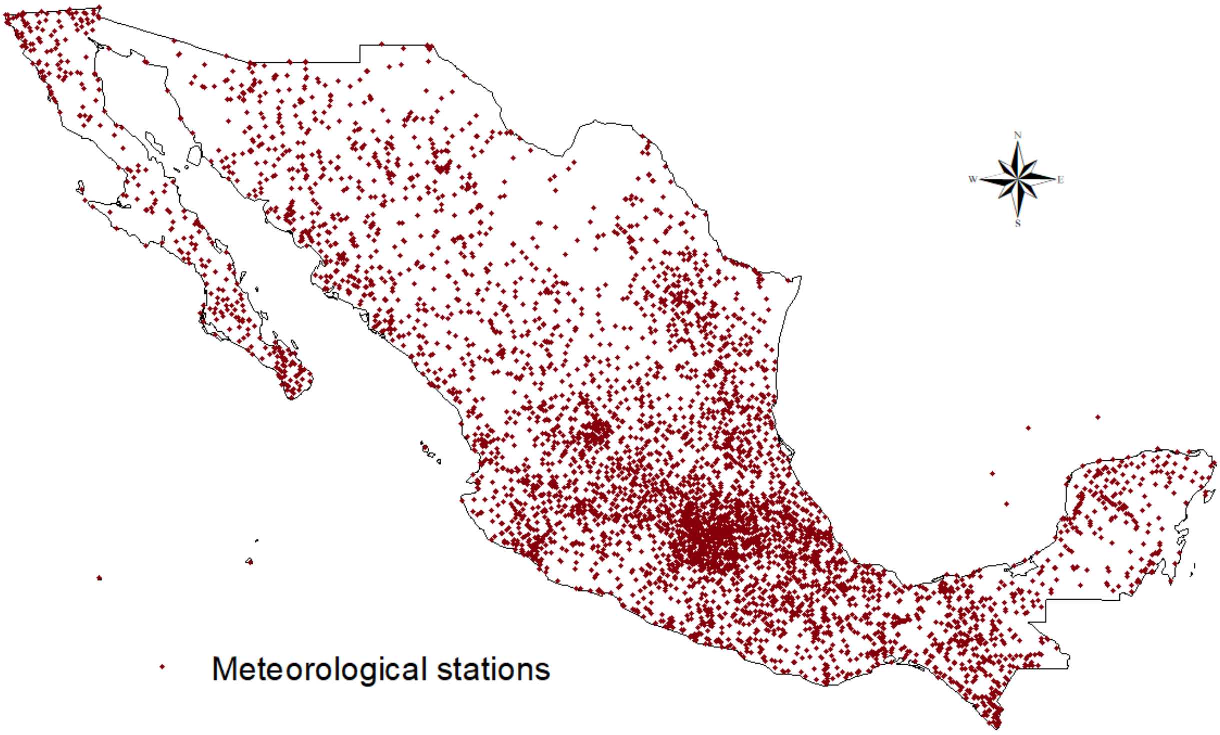



**Figure 2.5a. Meteorological stations**

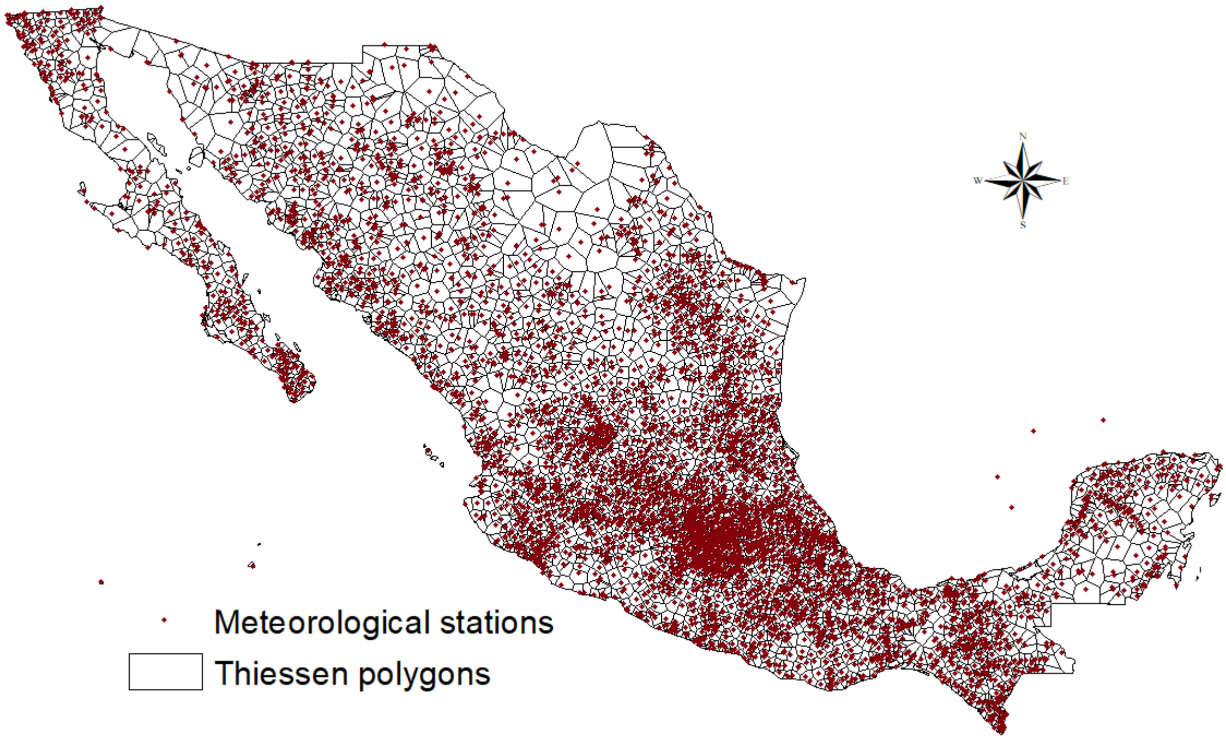



**Figure 2.5b. Thiessen polygons**

Source: own elaboration based on CLICOM project

The intersect tool in ArcGIS allows us to extract values from Thiessen polygons for each point in the points-layer created in the previous step ($1km^2$). To add these climate variables to the original database, we use the same matching criteria as for data in Hijmans et al. (2005). For CAs larger than $1km^2$, we take the average value of points within the same control area. For CAs smaller than $1km^2$, we use the value at the centroid of the control area. Moreover, we use weighted averages using the area of the corresponding plots and total farmland area to transform plot-level data to farm-level data.

### *2.3.3.3. Characteristics of the soil*

Estimations of the Ricardian hedonic model also include the characteristics of the soil. INEGI publishes a soils' classification based on the Soil Map of the World (FAO-UNESCO, 1974, 1997). Following the World Reference Base (WRB) and INEGI's adjustments, this classification includes data on 4,418 soil profiles, chemical and physical analyses of 14,349 samples of land, and 1,901 photographs. These soils' profiles capture land features such as pH, CO, Colour, CE, CIC, % of arena, % of limo, and % of clay. It also contains topographical characteristics. However, using all these profiles in the analysis would be cumbersome, then, we use the general classification, which groups soils into 21 general types: Acrisol, Andosol, Arenosol, Cambisol, Castanozem, Chernozem, Feozem, Fluvisol, Gleysol, Litosol, Luvisol, Nitosol, Planosol, Ranker, Regosol, Rendzina, Solonchak, Solonetz, Vertisol, Xerosol and Yermosol.[65] To assign the type of soil to each plot of land in the sample, we intersect the $1km^2$ points-layer and the GIS-soils database in Figure 2.6a.[66] Figure 2.6b displays an example for a particular control area. There are 25 points ($25\ km^2$) within the control area, from which 6 points belong to litosols' area and 19 to vertisols' area. Thus, if the plot belongs to this control area, we assign 24% and 76% to the variables litosol and vertisol respectively.

**Figure 2.6 Soil types and control areas**

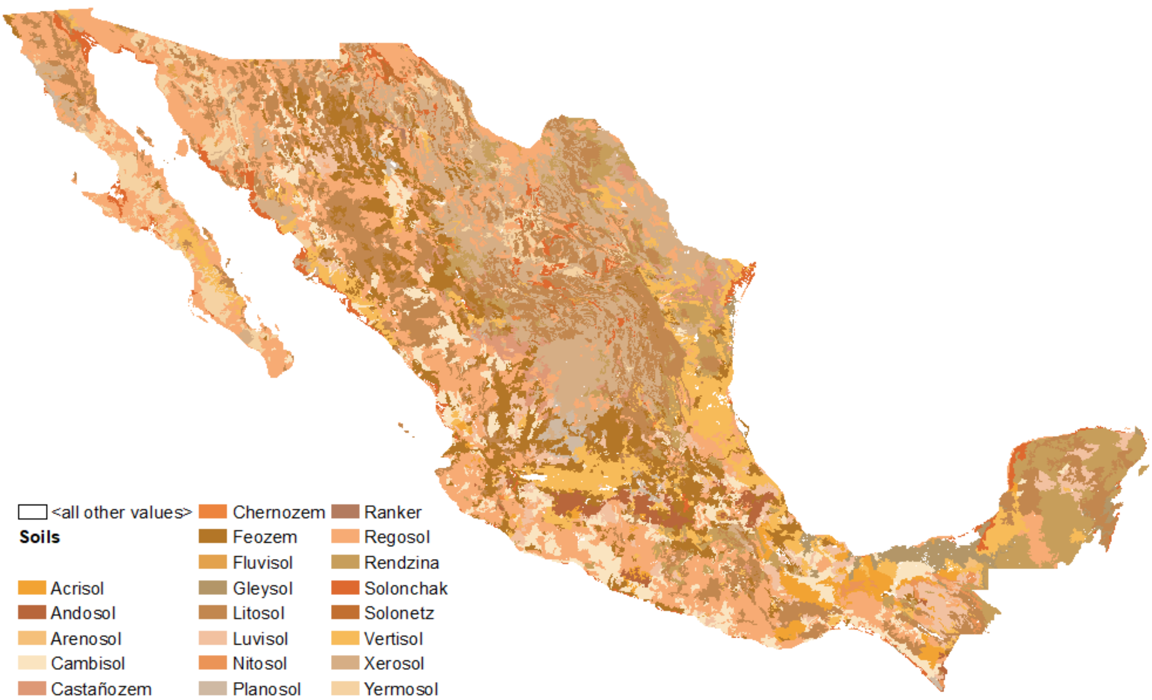



**Figure 2.6a. Soil types**

[65] For further details about the characteristics of these soil profiles see Appendix A2.4. Alternatively, the reader should refer to INEGI (2014b): http://www.inegi.org.mx/inegi/SPC/doc/INTERNET/EdafIII.pdf

[66] Same matching procedure as for climate data.

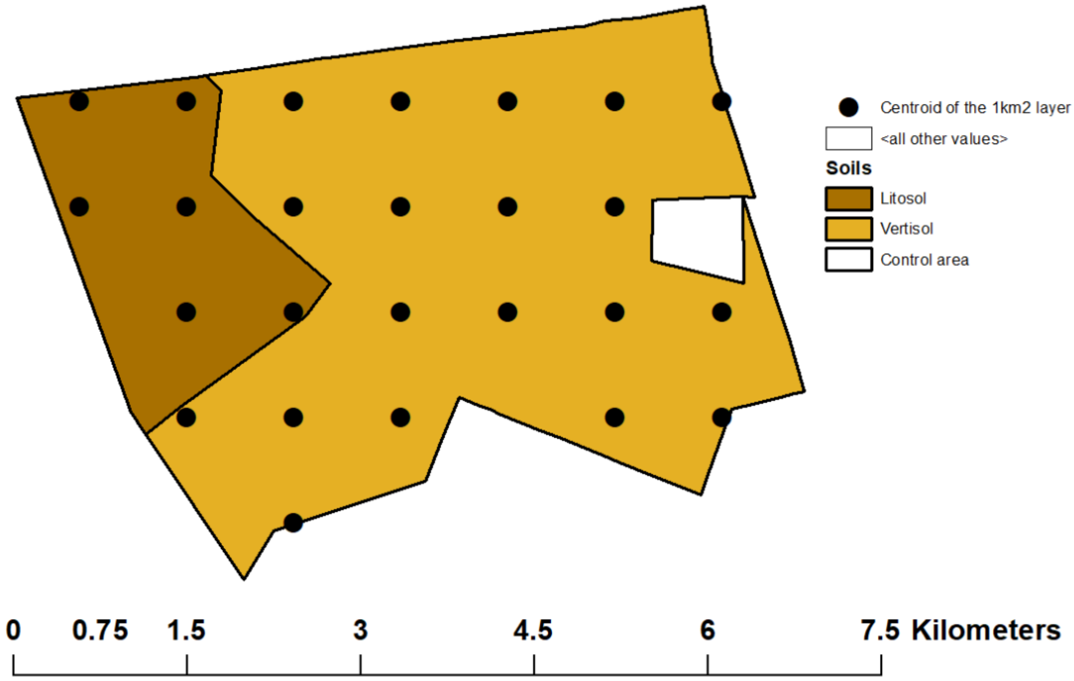



**Figure 2.6b. Soil types per control area**

Source: own elaboration based on INEGI (2014a)

To transform plot-level data to farm-level data, we use the same weighting procedure:

$$S_{ib} = \sum_{j=1}^{J} \frac{S_{ibj} * a_{ij}}{A_i}$$

where $S_{ib}$ is the percentage of farmland area classified as the $b$-th soil type and $S_{ibj}$ is the percentage of area of the control area where the plot is located classified as the $b$-th soil type.

### *2.3.3.4. Additional control variables*

Land rental prices and net revenues also depend on factors other than climate and soils. The set of additional control variables include utilised land, the Euclidean distance from the plot to the nearest urban area, the Euclidean distance from plot to the nearest permanent water body and river, road density in the surrounding area, irrigation, land tenure, and access to electricity. To add these control variables to our database, we combine data from the NAS and other GIS-databases.

For total utilised areas, the NAS reports owned and rented areas. INEGI publishes polygons-layers of urban areas, water bodies, and rivers. Using such polygons, we measure the straight line (Euclidean distance) between each point (~1km$^2$) within the control area to the nearest urban area, water body, and river and then, we take the average of all points within the same control area. Because farmers own/rent plots of land within different CAs, we compute the weighted averages of such distances using the proportion of land of the corresponding plot to total land as the weighting factor for climate data. Regarding road density, we use the ratio of roads' length (metres) to total area (square kilometres) in the corresponding municipality.

NAS also reports whether the plot has an irrigation system or not, if so, the irrigated area is also reported. This survey identifies five different land tenure regimes in Mexico: private (32% and 28% of the total number of plots in the 2012 and 2014 samples respectively), communal (4% and 3%), *ejidal* (62% and 66%),[67] colony (2.15% and 2.41%), and public (0.4% and 0.3%) properties. For irrigation and *ejidal* lands, we use the same procedure as for climate, soils, and distances to obtain farm-level weighted averages. For electricity, the NAS reports whether the farm has access to electricity or not.

After removing infeasible values and observations with missing data, 17,351 and 58,743 farms reports sufficient information to calculate net revenues per hectare in the 2012 and 2014 agricultural years respectively. The 2012 sample does not represent the entire sector because the NAS collects data on revenues and costs only from large farms (total utilised land equal to or larger than 20 hectares).[68] Conversely, the sample for 2014 represents the entire agriculture sector in Mexico. Regarding land rental prices, several farms do not usually rent land in Mexico.

[67] Portion of arable land, forests or water that the government allocates to groups of peasants after the Mexican Revolution in 1910-1921. Beneficiaries of this land allocation can harvest or rent these lands, and recently, they can sell them when the General Assembly of *ejidatarios* approves it.
[68] There are few farms (2,749) with less than 20 hectares in the 2012 sample because INEGI collects data on revenues and costs from farms within specific states.

Therefore, we only observe 2,388 and 5,301 farms renting at least one plot of land and 573 and 1,538 farms with 100% rented land in the corresponding years.

Tables 2.15 and 2.16 in Appendix A2.5 show the descriptive statistics of the abovementioned samples. Interestingly, the average net revenue per hectare in 2012 is $6,180 and -$5,420 in 2014. These figures suggest that, in average, annual expenses exceed revenues in most of Mexican farms, especially in small farms, which are not representative in the 2012 sample. In other words, the 2012 sample mainly includes data on large farms, which tend to be more efficient and therefore, are more likely to obtain higher positive net revenues. Aside from large farms in the 2012 sample, the 2014 survey collects data on small and self-consumption farms, which tend to be less efficient and are more likely to operate with negative net revenues. We believe that those farms remain in the market due to subsidy payments that aim to promote food security or the alleviation of poverty in rural areas. The corresponding ranges of net revenues per hectare are -$52,990-(+) $191,920 and -$159,980-(+) $217,320.

The huge variation of net revenues may arise because measurement errors (revenues and expenses) and the presence of unexpected events. For example, a catastrophic event such as a weather shock may reduce total output to zero and the farmer must still pay fixed and some variable costs. Furthermore, farmers may report enough information to calculate total revenue but may not provide sufficient information about the use of different forms of capital such as buildings, machinery, and equipment; therefore, we and other studies may overstate net revenues per hectare in this case.

The variation of land rental prices seems to be more stable than the variation of net revenues.[69] The rental price per hectare ranges between $500 and $53,580 and from $400 to $44,440 in the

[69] We compare the variation of both net revenues and rental prices in the following section.

2012 and 2014 agricultural years, respectively. In average, a farmer pays \$6,390 and \$5,070 per hectare of rented land in the corresponding samples (see Tables 2.15 and 2.16 in Appendix A2.5 for further details about the distribution of the remaining variables).

Taking into account expressions 2.11-2.12 in section 2.3 and data availability, the specifications of the Ricardian Hedonic model that we estimate in this chapter are as follows:

$$\pi_i^a = \beta_0 + \sum_{j=1}^{8} \beta_j F_{ij} + \sum_{j=1}^{6} \sum_{k=1}^{6} \beta_{jk} F_{ij} F_{ik} + \sum_{j=9}^{28} \beta_j S_{ij} + \sum_{j=29}^{37} \beta_j H_{ij} + \sum_{j=38}^{40} \beta_j FT_{ij} + \sum_{j=41}^{71} \beta_j FS_{ij} + u_i \quad (2.19)$$

$$R_i = \beta_0 + \sum_{j=1}^{8} \beta_j F_{ij} + \sum_{j=1}^{6} \sum_{k=1}^{6} \beta_{jk} F_{ij} F_{ik} + \sum_{j=9}^{28} \beta_j S_{ij} + \sum_{j=29}^{37} \beta_j H_{ij} + \sum_{j=38}^{40} \beta_j FT_{ij} + \sum_{j=41}^{71} \beta_j FS_{ij} + u_i \quad (2.20)$$

where, $\pi_i^a$ and $R_i$ are net revenues and rental prices per hectare (in their logarithm form); $\beta_0$ is the constant term; $F_j$ includes the linear terms of seasonal (six-month) temperature, rainfall, storms and clouds; $F_j F_k$ stands for square terms of seasonal temperature and rainfall, and it also includes the interactions between these two climate variables; $S_j$ comprises 20 soil profiles (excluding one category); $H_j$ includes 10 additional control variables (utilised area, square utilised area, distance to the nearest city, distance to the nearest water body, distance to the nearest river, road density, access to irrigation, land tenure regime and access to electricity); $FT_{ij}$ are farm type fixed effects (arable, beef cattle, dairy and mixed farms);[70] $FS_{ij}$ are 31 state fixed effects (excluding one state); $\beta_{jk} = \beta_{kj}$; and, $\beta_j$ are the corresponding parameters.

[70] We use a threshold of 2/3 of the total revenue derived from any of the 4 farm types to classify farms. For example, if a farm obtains 2/3 of its revenue from the production of beef cattle then we consider this farm as a beef cattle farm. When the farm does not derive 2/3 of its revenue from arable, dairy or beef cattle activities, we consider it as a mixed farm.

## 2.4. Results

To analyse the results from different specifications of the Ricardian model, we organise this sections as follows. First, since we do not observe land rental prices in all farms and the NAS-2012 only collected data on large farms, we use net revenues per hectare to estimate a Ricardian hedonic model for the entire sample in the NAS-2014. We also present the results for small-large, irrigated-rain-fed, ejidal-private, and crops-mixed-livestock farms. Second, we estimate a Ricardian hedonic model for those farmsteads in which we do observe both net revenues and land rental prices. The comparison between parameter estimates from these Ricardian models allows to test whether these models lead to different conclusions. Such differences may arise because net revenues suffer from measurement errors, e.g. due to lack of data on the cost of capital, or because are sensitive to weather shocks and therefore, do not measure land rents accurately. Rental prices may not reflect land rents properly if the government, or any other third party, intervenes in the rental price negotiation or if the rent is not fully paid at the beginning of the agricultural cycle. If such differences arise, future investigations need to rethink about the reliability of using net revenues to predict the effects of climate change on agriculture.[71] Third, using parameter estimates from the abovementioned Ricardian models, we speculate about the potential impact of climate change on Mexican farms.

To identify the best functional form of the Ricardian model, we perform a set of specification tests. We test whether the dependent variable should be in logs rather than in levels using a Box Cox transformation of the dependent variable. This transformation includes both the linear and the log-linear specifications as special cases (Cameron and Trivedi, 2011). The Box Cox transformation is defined as follows: $g(y_i, \theta) = (y_i^{\theta} - 1)/\theta = \boldsymbol{x}_i'\boldsymbol{\beta} + u_i$, where $u_i$ is assumed

[71] If researchers can overcome the abovementioned issues then, net revenues could measure land rents appropriately.

to follow a normal distribution with zero mean and constant variance. Under this transformation, the dependent variable can be either (i) $g(y,\theta) = y - 1$ if $\theta = 1$; (ii) $g(y,\theta) = \ln[y]$ if $\theta = 0$; and (iii) $g(y,\theta) = 1 - (1/y)$ if $\theta = -1$. Therefore, the log-linear model is preferred if $\hat{\theta}$ is close to zero and the linear model if $\hat{\theta}$ tends to one. Negative values in the net revenues variable deter us from testing for the functional form. However, we estimate a Box Cox model for land rental prices, which are strictly positive, using the model specification in equation (2.12) and encounter that $\hat{\theta}_{2012} = 0.21$ and $\hat{\theta}_{2014} = 0.14$.[72] These values are close to zero; therefore, the log-linear functional form may be preferred for the rental price equation. To be consistent with the specification of the Ricardian model in this section, we use also a log-linear model for net revenues.[73]

To avoid multicollinearity, we demeaned all variables and use six-monthly rather than quarterly climate values.[74] Apart from climate, we test the appropriateness of including additional controls in the Ricardian model. We find that the characteristics of the soil, farm size, distance to the nearest city, distance to the nearest water body, distance to the nearest river, road density, irrigation, land tenure, electricity, farm type, and state fixed effects are, indeed, statistically important in all models.[75]

[72] Both coefficients are statistically significant at the 1% significance level.

[73] To deal with negative values of net revenues, we use the *neglog* transformation of net revenues (see John and Draper (1980) and Whittaker et al., (2005), which is defined as: $\ln[nr] = (sign(nr_i) * \ln[|nr_i|]$, where $nr_i$ is the net revenue of the corresponding farm.

[74] The mean Variance Inflation Factor (VIF) test suggests that using three-monthly values and non-demeaned values lead to high VIFs. For example, the mean VIF for the net revenues model (entire sample in 2014) with non-demeaned and quarterly climate values is 360.03 and it goes down when we demeaned all variables (28.22). The mean VIF for the model with six-monthly values and demeaned variables is 5.60 (and 83.19 when we do not demean all variables). Such result is consistent in all Ricardian models (See Tables 2.17-2.22 in the Appendix A2.5). Therefore, we use six-monthly and demeaned values in all Ricardian models.

[75] Using the largest sample of farms (net revenues in 2014), we encounter that six-monthly temperature and rainfall terms are jointly significant (F-statistic (10, 58663) = 62.95). We also find that additional climate variables such as the number of days with hail, storms and clouds are jointly significant (F-statistic (6, 58663) = 11.62). The same results for 21 soil profiles (F-statistic (20, 58663) = 7.98), additional control variables (F-statistic (9, 58663) = 138.25) and state and farm type fixed effects (F-statistic (34, 58663) = 77.51). These results are consistent in all models, including rental price equations.

### *2.4.1. Ricardian model using net revenues*

Table 2.4 shows the parameter estimates of the Ricardian hedonic model for the entire sample in the NAS-2014. To identify heterogeneous effects of climate (and other explanatory variables) on net revenues, we estimate Ricardian models for different subsamples. The results in Table 2.4 suggest that there exists a non-linear relationship between temperature-rainfall and net revenues. This finding is in line with previous empirical studies.[76] Similar to Fezzi and Bateman (2015), we find significant non-linear interaction effects; additional rainfall benefits (harms) those lands with increased (reduced) heat stress in the spring-summer (autumn-winter) season. Mendelsohn et al. (2010) encounter that most of interactions terms are not significant. In this regard, Galindo et al. (2015) do not include interaction terms in the Ricardian hedonic model for the Mexican agriculture. According to Fezzi and Batemand (2015), such omission leads to important biases in the parameter estimates of the Ricardian model.

To control for other climatic conditions, we include the number of days with storms and dense clouds in the Ricardian model. Table 2.4 shows that as the frequency of storms rises in the spring-summer (autumn-winter) season, net revenues go down (go up). In average, one additional storm-day leads to a 1.38% reduction (4.68% increase) in net revenues per hectare in the spring-summer (autumn-winter) season. This finding suggests that large quantities of rain in a single day harm land productivity, especially in the growing phase.[77] Perhaps some crops cannot tolerate more abundant and unexpected rain in the spring-summer season.[78] In contrast, such events benefit land productivity in the autumn-winter season. Given that, rainfall in the

[76] Mendelsohn et al. (2010) encounter an inverted U-shaped (U-shaped) relationship between winter and summer (spring and autumn) temperature and land values in Mexico. Rainfall and net revenues hold an inverted U-shaped relationship in spring, summer and autumn. Galindo et al. (2015) identify an inverted U-shaped (U-shaped) relationship between spring and summer (winter and autumn) temperature and municipality-level net revenues. Rainfall and net revenues hold an U-shaped (inverted U-shaped) relationship in winter, summer and autumn (spring).

[77] In average, we observe 576 mm. of rain in the spring-summer season. Rain is more abundant in the July-September period, which coincides, for example, with the growing phase of maize, which is the most popular crop in Mexico.

[78] Typically, the farmer does not know the temporal distribution of storms.

autumn-winter season represents 39% of annual rainfall and the number of days with storms represent one third of the annual figure, additional rain reduce the necessity of using irrigation and consequently, increase net revenues, even if such events are unexpected. Days with dense clouds are not statistically significant in the entire sample. This might indicate that sporadic reductions in daylight do not alter net revenues.

Unlike previous studies in Mexico,[79] the geographical coverage of the NAS-2014 sample allows us to include all soil types in the Ricardian model. The main findings indicate that higher shares of land classified as Acrisol, Andosol, Luvisol and Rendzina*,* lead to higher net revenues. Although the level of nutrients in Acrisol soils is low, these soils are suitable for the production of cacao, coffee, pineapple and pastures in tropical zones. The volcanic origin of Andosol permits moisture retention. Such feature significantly increases yields of avocado plantations in Michoacan. Similar to Acrisol and Andosol soils, Luvisol soils are suitable for the production of tropical fruits, avocado and pastures. The superficial layer of organic matter of Rendzina soils permits the cultivation of maize with reasonable yields. Other soils such as Arenosol, Castanozem, Chernozem, Fluvisol, Litosol, Regosol and Yermosol reduce net revenues. Among other things, this happens because Arenosol soils contains more than 65% of sand and have low capacity of moisture retention. Fluvisol soils contain sand and stones, which makes them less suitable for agriculture activities. Litosol soils are usually utilised for grazing activities, especially for sheep production, and are not suitable for the majority of crops in our sample.[80] Regosol soils come from stones, and consequently, have low levels of organic matter. Moreover, Yermosol soils characterise desert areas in Mexico (INEGI, 2014b). For the remaining soil profiles, their effects on net revenues are either statistically irrelevant or

[79] Mendelsohn et al (2010) include a subset of 13 out of 21 soil profiles (6 profiles in what they called the 'parsimonious model'). Galindo et al (2015) do not include the characteristics of the soil at all.
[80] These soils are suitable for the production of maize and Nopal (cactus) but with low to moderate yields.

inconclusive and depends on the corresponding soil subtypes. For some soil types, the availability of irrigation matters, e.g. Acrisol, Andosol, Nitosol and Ranker (see the Ricardian model for irrigated farms).

Most of the studies using net revenues to proxy land rents assume a linear and monotonic relationship between net revenues and farmland (utilised land).[81] Parameter estimates in Table 2.4 show that there exists a non-linear (inverted U-shaped) relationship between net revenues and farmland. This finding is not in line with Galindo et al[82] and Mendelsohn et al's[83] findings for Mexican farms. However, this result suggests that putting more land into cultivation and grazing activities increases net revenues of smaller farms up to a certain farm size at which further additions of land cause net revenue losses. We believe that landowners tend to rent land with poor quality in land markets; otherwise, they would cultivate or exploit such fields, therefore land repackaging is costly (Maddison, 2000; Mendelsohn et al., 2010).

Distances from the plot to the nearest water body and river hold the expected relationship, except for small farms. The Euclidean distance from the plot to the water body is statistically significant at the 1% significance level and suggests that one km. closer to the water source rises net revenues by approximately 0.49%. Proximity to rivers does not alter net revenues in the full-sample model. Although some farmers might pump water from rivers to irrigate their lands, the National Water Commission (CONAGUA by its acronym in Spanish) does not typically allow individual farmers to do it. Instead, CONAGUA allocates permits to farmers to irrigate their lands using existing damns (water bodies). Under such circumstances, proximity to rivers might not be relevant.

[81] Such investigations either ignored the effect of farm size on net revenues per unit of land or included only the linear term.
[82] Square terms of cropland are not statistically significant.
[83] These authors encounter a U-shaped relationship between farm size and land values.

According to Table 2.4, farms located further away from urban areas observe higher net revenues. The associated coefficient to the Euclidean distance from the plot to the nearest city is significant at the 1% significance level and indicates that one extra km. away from the city increases net revenues by 1.48%, in average. Such an effect is not in line with our original expectations. Previous studies found the opposite direction of this relationship (see for example Mendelsohn et al. (2010)). Net revenues might suffer from measurement errors and might not reflect land rents. This could happen if the net revenues variable does not (correctly) account for transportation costs, e.g. fuel and freight charges. We further investigate this finding using land rental prices in the following section. Road density reduces net revenues and such an effect is statistically significant at the 1% significance level. An extra $m/km^2$, in the municipality where the plot is located, shrinks net revenues by approximately 0.13%. This result also contradicts our initial expectations since a denser road network presumably increases the demand for land and, consequently, land prices. Thus, we think this happens because net revenues suffer from measurement errors and do not capture land values. Alternatively, annual expenses of farms within urban areas, e.g. wages, may increase more than revenues thereby; net revenues would be smaller in such cases.

As expected, irrigation facilities increase net revenues in all cases. The existence of an irrigation system in the corresponding field is a desirable land attribute, especially in those areas with unreliable rainfall. The associated coefficient suggests that 1% extra irrigated-land rises net revenues by 2.16% as in Mendelsohn et al. (2010). Similarly, an electricity grid is a desirable land attribute. It allows farmers to use existing technologies more efficiently, e.g. electric irrigation systems. Seo and Mendelsohn (2008b) and Seo and Mendelsohn (2008d) encounter the same effect in Latin American farms. The only exception are small farms, which show the opposite effect. In this case, the cost of electricity might exceed the benefits of using it. Finally, agricultural lands under the *ejidal* regime observe lower net revenues. In average, net revenues, in farms with ejidal titles, are 1.28% lower than in private or in other tenure regimes. Although, the land reform (ejido) gave landowners the right to use ejidal lands as collaterals (Johnson, 2001), which is a desirable land attribute, the relationship between such land reform and land productivity remains inconclusive in the existing literature (Heath, 1992). We further examine this relationship in the following section using land rental prices.

## Table 2.4 Ricardian hedonic models 2014

| | Farms | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **All** | **Small** | **Large** | **Irrigated** | **Rain-fed** | **Ejidal** | **No ejidal** | **Arable** | **Mixed** | **Livestock** |
| | | | | | **Climate** | | | | | |
| *Temp. spsu* | 0.407*** | 0.218*** | 0.215*** | 0.682*** | 0.362*** | 0.533*** | 0.203** | 0.307*** | 0.512*** | -0.165 |
| | (0.055) | (0.083) | (0.080) | (0.107) | (0.069) | (0.072) | (0.094) | (0.082) | (0.096) | (0.208) |
| *Temp. spsu sq.* | -0.019*** | -0.010 | -0.022** | 0.003 | -0.020*** | -0.021*** | -0.020** | -0.000 | -0.021** | -0.036* |
| | (0.006) | (0.007) | (0.010) | (0.014) | (0.006) | (0.007) | (0.009) | (0.008) | (0.011) | (0.021) |
| *Temp. auwi* | -0.173*** | -0.044 | -0.110 | -0.343*** | -0.184** | -0.306*** | 0.006 | -0.180** | -0.302*** | 0.320* |
| | (0.060) | (0.090) | (0.084) | (0.116) | (0.074) | (0.078) | (0.104) | (0.092) | (0.103) | (0.191) |
| *Temp. auwi sq.* | 0.032*** | 0.019*** | 0.017* | 0.045*** | 0.018*** | 0.038*** | 0.021** | 0.014* | 0.040*** | 0.011 |
| | (0.005) | (0.007) | (0.009) | (0.012) | (0.006) | (0.007) | (0.009) | (0.008) | (0.010) | (0.018) |
| *Rainfall spsu* | 0.363*** | 0.312*** | 0.421*** | 0.117 | 0.444*** | 0.203*** | 0.592*** | 0.068 | 0.550*** | 0.073 |
| | (0.047) | (0.059) | (0.081) | (0.122) | (0.050) | (0.064) | (0.073) | (0.073) | (0.072) | (0.138) |
| *Rainfall spsu sq.* | -0.021*** | -0.020*** | -0.028*** | -0.011 | -0.027*** | -0.019*** | -0.026*** | 0.001 | -0.036*** | -0.012 |
| | (0.002) | (0.003) | (0.005) | (0.010) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.011) |
| *Rainfall auwi* | -0.110* | 0.052 | 0.009 | -0.176 | -0.100 | 0.059 | -0.335*** | -0.259*** | -0.214** | -0.054 |
| | (0.061) | (0.077) | (0.107) | (0.196) | (0.063) | (0.086) | (0.093) | (0.096) | (0.089) | (0.154) |
| *Rainfall auwi sq.* | 0.016*** | 0.016*** | 0.012** | 0.030* | 0.011** | 0.013** | 0.022*** | 0.010 | 0.026*** | -0.002 |
| | (0.004) | (0.006) | (0.006) | (0.017) | (0.004) | (0.006) | (0.006) | (0.008) | (0.006) | (0.009) |
| *Temp.*Rain. spsu* | 0.012* | 0.010 | 0.016 | 0.045** | -0.003 | 0.024*** | 0.000 | 0.012 | -0.011 | 0.013 |
| | (0.007) | (0.008) | (0.013) | (0.018) | (0.008) | (0.009) | (0.011) | (0.010) | (0.011) | (0.034) |
| *Temp.*Rain. aiwi* | -0.023*** | -0.037*** | -0.038** | 0.000 | 0.002 | -0.051*** | -0.003 | 0.011 | -0.010 | 0.054 |
| | (0.008) | (0.010) | (0.019) | (0.032) | (0.009) | (0.013) | (0.012) | (0.012) | (0.014) | (0.036) |
| | | | | | **Other climate variables** | | | | | |
| *Storms Sp-Su* | -0.014* | -0.001 | -0.030** | -0.014 | -0.012 | -0.015 | -0.014 | -0.011 | -0.005 | 0.047** |
| | (0.008) | (0.010) | (0.014) | (0.019) | (0.009) | (0.011) | (0.014) | (0.012) | (0.014) | (0.024) |
| *Storms Au-Wi* | 0.047*** | 0.037* | 0.058** | 0.071** | 0.034** | 0.054*** | 0.030 | 0.052** | 0.036 | -0.050 |
| | (0.014) | (0.019) | (0.023) | (0.033) | (0.016) | (0.018) | (0.024) | (0.021) | (0.023) | (0.044) |
| *Clouds Sp-Su* | -0.001 | 0.003 | -0.005 | 0.003 | 0.004 | 0.010** | -0.016** | -0.004 | 0.011 | -0.000 |
| | (0.004) | (0.005) | (0.007) | (0.010) | (0.004) | (0.005) | (0.007) | (0.006) | (0.007) | (0.012) |
| *Clouds Au-Wi* | -0.002 | -0.009 | 0.006 | -0.019 | -0.002 | -0.013** | 0.013* | -0.009 | -0.012 | 0.013 |
| | (0.005) | (0.006) | (0.008) | (0.014) | (0.005) | (0.006) | (0.008) | (0.007) | (0.008) | (0.012) |
| | | | | | **Soils** | | | | | |
| *Acrisol* | 0.009*** | 0.008** | 0.008 | 0.032*** | 0.003 | 0.012*** | 0.008* | 0.024*** | -0.014*** | 0.025*** |
| | (0.003) | (0.003) | (0.005) | (0.007) | (0.003) | (0.004) | (0.005) | (0.006) | (0.004) | (0.008) |
| *Andosol* | 0.008*** | 0.005 | 0.029*** | 0.040*** | 0.004 | 0.006 | 0.008* | 0.001 | -0.001 | -0.012 |
| | (0.003) | (0.003) | (0.008) | (0.007) | (0.003) | (0.004) | (0.004) | (0.003) | (0.005) | (0.020) |
| *Arenosol* | -0.021 | -0.143*** | -0.020 | | -0.020 | 0.039 | -0.045** | 0.000 | -0.130*** | 0.010 |
| | (0.018) | (0.009) | (0.018) | | (0.018) | (0.027) | (0.020) | (0.014) | (0.013) | (0.017) |
| *Cambisol* | -0.001 | -0.000 | 0.001 | 0.002 | -0.000 | -0.002 | -0.002 | 0.006** | -0.012*** | 0.011** |
| | (0.002) | (0.002) | (0.003) | (0.004) | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.005) |
| *Castanozem* | -0.013*** | -0.016*** | -0.006* | -0.010** | -0.015*** | -0.012*** | -0.013*** | -0.004 | -0.023*** | -0.021** |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.003) | (0.004) | (0.004) | (0.003) | (0.005) | (0.010) |
| *Chernozem* | -0.061*** | -0.031 | -0.091*** | 0.062 | -0.069*** | -0.064*** | -0.049 | -0.041** | -0.083** | -1.985*** |
| | (0.017) | (0.030) | (0.023) | (0.103) | (0.014) | (0.019) | (0.034) | (0.017) | (0.041) | (0.204) |
| *Feozem* | -0.000 | 0.002 | -0.001 | -0.002 | 0.002 | -0.001 | -0.000 | -0.003 | -0.006*** | 0.003 |
| | (0.001) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.006) |
| *Fluvisol* | -0.023*** | -0.020** | -0.008 | -0.044** | -0.011 | -0.030*** | -0.013 | -0.017** | -0.031* | -0.016 |
| | (0.007) | (0.008) | (0.016) | (0.017) | (0.008) | (0.009) | (0.013) | (0.008) | (0.016) | (0.043) |
| *Gleysol* | 0.003 | 0.010 | 0.004 | -0.005 | 0.004 | 0.006 | -0.001 | 0.009 | -0.012* | 0.001 |
| | (0.004) | (0.006) | (0.005) | (0.021) | (0.004) | (0.005) | (0.006) | (0.008) | (0.006) | (0.007) |
| *Litosol* | -0.008*** | -0.003 | -0.006** | -0.022*** | -0.004* | -0.007*** | -0.013*** | -0.005** | -0.011*** | -0.005 |
| | (0.002) | (0.003) | (0.003) | (0.005) | (0.002) | (0.002) | (0.003) | (0.003) | (0.004) | (0.006) |
| *Luvisol* | 0.002 | 0.001 | 0.012*** | -0.002 | 0.003 | -0.001 | 0.006* | -0.000 | -0.008*** | 0.016** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (0.002) | (0.002) | (0.004) | (0.005) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.007) |
| *Nitosol* | -0.009 | -0.013 | -0.003 | 0.078*** | -0.012* | 0.006 | -0.030** | 0.004 | -0.026** | 0.025** |
| | (0.007) | (0.010) | (0.009) | (0.017) | (0.007) | (0.008) | (0.013) | (0.011) | (0.013) | (0.012) |
| *Planosol* | -0.003 | -0.007** | -0.006 | -0.012*** | 0.003 | -0.007* | 0.002 | -0.005 | -0.006 | 0.026 |
| | (0.003) | (0.003) | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (0.005) | (0.017) |
| *Ranker* | 0.170 | -2.047*** | 0.216 | 2.344** | 0.075 | -0.120* | 1.536*** | 4.059*** | -0.424 | 0.090** |
| | (0.156) | (0.097) | (0.168) | (1.158) | (0.058) | (0.071) | (0.579) | (0.398) | (2.143) | (0.046) |
| *Regosol* | -0.009*** | -0.008*** | -0.001 | -0.008** | -0.008*** | -0.008*** | -0.009*** | 0.008*** | -0.025*** | 0.007 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.005) |
| *Rendzina* | 0.005** | 0.007** | 0.005 | -0.002 | 0.007*** | 0.005* | 0.001 | 0.002 | -0.001 | 0.004 |
| | (0.002) | (0.003) | (0.003) | (0.005) | (0.002) | (0.003) | (0.004) | (0.003) | (0.004) | (0.005) |
| *Solonchak* | 0.003 | 0.017** | -0.005 | -0.012* | 0.014*** | -0.002 | 0.008 | 0.004 | -0.010 | -0.013 |
| | (0.004) | (0.007) | (0.005) | (0.007) | (0.005) | (0.005) | (0.007) | (0.006) | (0.007) | (0.011) |
| *Solonetz* | 0.036 | 0.050 | 0.031 | 0.033 | 0.038 | 0.003 | 0.053 | 0.059 | -0.127 | 0.075*** |
| | (0.035) | (0.038) | (0.053) | (0.064) | (0.035) | (0.063) | (0.054) | (0.054) | (0.102) | (0.023) |
| *Xerosol* | -0.001 | -0.009*** | 0.002 | -0.004 | -0.001 | -0.004* | 0.003 | 0.003 | -0.010*** | 0.000 |
| | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.006) |
| *Yermosol* | -0.009* | -0.005 | -0.009 | -0.019*** | 0.009 | -0.019*** | -0.004 | -0.017** | -0.023*** | 0.011 |
| | (0.005) | (0.012) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.008) | (0.008) | (0.010) |
| | | | | | **Control variables** | | | | | |
| *Area*1,000* | 0.580*** | 0.225*** | 0.491*** | 1.076*** | 0.654*** | 2.674*** | 0.543*** | 3.352*** | 1.878*** | 0.342*** |
| | (0.052) | (0.012) | (0.045) | (0.186) | (0.069) | (0.341) | (0.053) | (0.712) | (0.326) | (0.052) |
| *Area*1,000 sq.* | -0.006*** | -0.014*** | -0.005*** | -0.009*** | -0.011*** | -0.141*** | -0.005*** | -0.028*** | -0.116*** | -0.005*** |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.003) | (0.036) | (0.001) | (0.006) | (0.040) | (0.001) |
| *City* | 0.015*** | -0.003 | 0.008 | 0.016** | 0.008* | 0.006 | 0.020*** | 0.019*** | 0.007 | 0.015* |
| | (0.004) | (0.007) | (0.005) | (0.008) | (0.004) | (0.005) | (0.006) | (0.005) | (0.007) | (0.008) |
| *Water body* | -0.005*** | -0.001 | -0.004* | -0.001 | -0.008*** | -0.000 | -0.012*** | -0.007*** | -0.008*** | -0.003 |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.005) |
| *River* | -0.001 | 0.010*** | -0.006** | 0.003 | -0.007*** | -0.002 | 0.000 | -0.001 | 0.009*** | -0.016*** |
| | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.005) |
| *Road density* | -0.001*** | -0.000* | -0.000 | -0.000 | -0.002*** | -0.001*** | -0.002*** | -0.001*** | -0.002*** | -0.002** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| *Irrigation* | 0.022*** | 0.022*** | 0.025*** | | | 0.019*** | 0.027*** | 0.020*** | 0.018*** | |
| | (0.001) | (0.001) | (0.002) | | | (0.001) | (0.002) | (0.001) | (0.002) | |
| *Ejidal* | -0.013*** | -0.002** | -0.014*** | -0.018*** | -0.010*** | | | -0.011*** | -0.013*** | -0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | | | (0.001) | (0.001) | (0.002) |
| *Electricity* | 0.702*** | -0.494*** | 0.584*** | 0.776*** | 0.186 | 0.617*** | 0.756*** | 0.685*** | 0.427*** | -0.206 |
| | (0.098) | (0.147) | (0.131) | (0.144) | (0.141) | (0.133) | (0.149) | (0.149) | (0.154) | (0.258) |
| Constant | -2.758*** | -3.937*** | -1.128*** | -3.632*** | -2.370*** | -3.634*** | -1.349*** | -5.758*** | -2.566*** | 1.252 |
| | (0.242) | (0.341) | (0.356) | (0.462) | (0.280) | (0.309) | (0.392) | (0.253) | (0.441) | (1.309) |
| Farm types (FE) | YES | YES | YES | YES | YES | YES | YES | NO | YES | NO |
| States (FE) | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 58,743 | 35,476 | 23,267 | 20,916 | 37,827 | 36,826 | 21,917 | 30,430 | 23,430 | 4,883 |
| R-squared | 0.111 | 0.105 | 0.074 | 0.082 | 0.130 | 0.106 | 0.120 | 0.111 | 0.091 | 0.085 |

Dependent variable: logarithm of net revenues per hectare (sign(net rev./ha)*ln(|net rev./ha|)
Small: farms with less than 20 hectares of land; large: farms with 20 or more than 20 hectares; irrigated: farms with some of their land with an irrigation system; rain-fed: none of the agricultural fields has an irrigation system; ejidal: some land in these farms is under the ejido's land tenure regime. FE: fixed effects.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5 shows the marginal effects (implicit prices) of six-monthly temperature and rainfall on net revenues. We fixed the remaining explanatory variables at their corresponding means. The set of F-tests at the bottom of Table 2.5 suggests that implicit prices of an additional degree Celsius in all types of farms, except for livestock, are statistically different from zero at the 1% significance level. The same results hold for an additional mm. of rainfall, except for irrigated and livestock farms for which additional rain in any of the agricultural seasons does not influence net revenues. We also encounter that small and large farms are equally sensitive to changes on temperature and/or rainfall. However, implicit prices of such climate variables differ between irrigated and rain-fed farms, between ejidal and non-ejidal lands, and between arable and pastoral farms.

The results also indicate that warmer (colder) environments would be beneficial for farming activities in the spring-summer (autumn-winter) season. Mendelsohn et al. (2010) identify negative (positive) marginal effects of one extra degree Celsius in the spring-summer (autumn-winter) season in all, irrigated, rain-fed, large, and small (all, rain-fed, large and small) farms. Unlike Mendelsohn et al, who use farm-level data on land values, Galindo et al. (2015) encounter a positive marginal effect of an extra degree Celsius in the spring-summer season in rain-fed farms (negative effects in the full sample and irrigated farms). Thus, the results from the net revenues equation in Table 2.5 are not in line with previous investigations in Mexico examining the effect of temperature on land rents.

**Table 2.5 Marginal effects of climate 2014**

| | Farms | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **All** | **Small** | **Large** | **Irrigated** | **Rain-fed** | **Ejidal** | **No ejidal** | **Arable** | **Mixed** | **Livestock** |
| | | | | | **Climate** | | | | | |
| *Temperature Sp-Su* | 0.407*** | 0.218*** | 0.215*** | 0.682*** | 0.362*** | 0.533*** | 0.203** | 0.307*** | 0.512*** | -0.165 |
| | (0.055) | (0.083) | (0.080) | (0.107) | (0.069) | (0.072) | (0.094) | (0.082) | (0.096) | (0.208) |
| *Temperature Au-Wi* | -0.173*** | -0.044 | -0.110 | -0.343*** | -0.184** | -0.306*** | 0.006 | -0.180** | -0.302*** | 0.320* |
| | (0.060) | (0.090) | (0.084) | (0.116) | (0.074) | (0.078) | (0.104) | (0.092) | (0.103) | (0.191) |
| *Rainfall Sp-Su* | 0.363*** | 0.312*** | 0.421*** | 0.117 | 0.444*** | 0.203*** | 0.592*** | 0.068 | 0.550*** | 0.073 |
| | (0.047) | (0.059) | (0.081) | (0.122) | (0.050) | (0.064) | (0.073) | (0.073) | (0.072) | (0.138) |
| *Rainfall Au-Wi* | -0.110* | 0.052 | 0.009 | -0.176 | -0.100 | 0.059 | -0.335*** | -0.259*** | -0.214** | -0.054 |
| | (0.061) | (0.077) | (0.107) | (0.196) | (0.063) | (0.086) | (0.093) | (0.096) | (0.089) | (0.154) |
| F-test (Temperature=0) | 177.36*** | 67.33*** | 9.07*** | 71.90*** | 85.20*** | 99.55*** | 46.44*** | 25.23*** | 46.04*** | 2.59 |
| Prob > F | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.88 |
| F-test (Rainfall=0) | 47.50*** | 69.99*** | 34.63*** | 0.18 | 89.18*** | 25.75*** | 20.06*** | 10.18*** | 37.72*** | 0.02 |
| Prob > F | 0.00 | 0.00 | 0.00 | 0.68 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.11 |
| F-test (Marginal effects are equal) | | 4.21 | | 39.05*** | | 25.21*** | | | 11.54**(+) | |
| Prob > F | | 0.38 | | 0.00 | | 0.00 | | | 0.02 | |
| Farm types (FE) | YES | YES | YES | YES | YES | YES | YES | NO | YES | NO |
| States (FE) | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 58,743 | 35,476 | 23,267 | 20,916 | 37,827 | 36,826 | 21,917 | 30,430 | 23,430 | 4,883 |

Small: farms with less than 20 hectares of land; large: farms with 20 or more than 20 hectares; irrigated: farms with some of their land with an irrigation system; rain-fed: none of the agricultural fields has an irrigation system; ejidal: some land in these farms is under the ejido's land tenure regime. FE: fixed effects.
(+) Marginal effects are the same for arable and livestock farms
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regarding rainfall, a wetter (drier) context would increase (reduce) net revenues in the spring-summer (autumn-winter) season. In this regard, Mendelsohn et al also encounter a positive (negative) marginal effect of one extra mm. of rainfall in the spring-summer (autumn-winter) season in all, irrigated, rain-fed, large, and small (all, irrigated, rain-fed, large, and small) farms. Conversely, Galindo et al encounter negative marginal effects of an additional mm. of rainfall in all, irrigated, and rain-fed farms in both seasons. Therefore, the results in Table 2.5 about the effect of rainfall on land rents are similar to those in Mendelsohn et al.

The exclusion of both nonlinear interaction effects between temperature and rainfall and the characteristics of the soil, e.g. moisture retention, slope, salinity, etc., in the Ricardian hedonic models in Galindo et al (2015) might explain the differences in marginal effects of rainfall on net revenues with respect to our results and those in Mendelsohn et al. (2010). Regarding temperature, there are two possible explanations for the contradictory results. First, simply because the sample in this study is in any aspect superior to those in previous studies and includes farms from the entire territory rather than a small sample of farms or aggregated municipality-level data, which produce a vast variety of agricultural commodities. Within these commodities, there should be crops and livestock species that tolerate warmer environments, especially in the spring-summer season.[84] Second, measurement errors and the huge variation in the net revenues variable might also cause such differences. Therefore, we investigate this possibility in the next section by comparing parameter estimates and marginal effects of climate variables using both net revenues and land rental prices for the same sample of farmsteads.

[84] We address this issue (adaptation strategies via crop or livestock switching) in the next chapter. In this regard, Mendelsohn et al. (2010) use data on farms that report ‘some’ crop production. It is not clear whether these authors use both crop and livestock production in their article. Galindo et al. (2015) use crop production in their analysis.

### *2.4.2. Net revenues and land rental prices*

Previous studies using farm-level data on net revenues reported low values of the R-squared associated to the Ricardian hedonic model. Among others, Kabubo and Karanja (2007), Eid et al. (2007), Fleischer et al. (2008), Wang et al. (2009), Seo et al. (2009), Kurukulasuriya et al. (2006) and Mendelsohn (2014) reported R-squared values of 0.12, 0.18-0.22, 0.19-0.22, 0.16-0.21, 0.12, 0.16 and 0.21 respectively.[85] Conversely, studies using farm-level data on land values tend to report higher R-squared values. For example, Mendelsohn et al. (2010) and Maddison (2000) reported R-squared values of 0.47-0.64 and 0.62, respectively. The set of explanatory variables does not remarkably vary from one study to another. Thereby, we believe that such variables are not able to explain the huge variation of net revenues.

Table 2.4 shows that the set of independent variables in the Ricardian models explains only 7%-13% of the total variation of net revenues in Mexico. Because such variation might arise from measurement errors or unexpected events occurring during the agricultural year, we use land rental prices to verify the abovementioned results. We observe 2,388 (573) and 5,301 (1,538) farms that rented at least one plot of land (rented 100% of their land) and report both land rental prices and net revenues in the NAS-2012 and the NAS-2014 respectively. Taking advantage of such information, we test for the appropriateness of using net revenues to assess the effect of climate change in developing countries.

Figures 2.7a (2.7b) and 2.7e (2.7f) display net revenues and land rental prices per hectare of the 2,388 (573) and 5,301 (1,538) farms with at least one rented plot (with 100% rented land). There is a huge variation in the distribution of net revenues compared to the distribution of land rental prices. Figures 2.7c (2.7d) and 2.7g (2.7h) show the large differences between net revenues and rental prices in the corresponding samples. In theory, these values should be along

[85] The remaining studies in the literature review report similar values.

the zero line. As we stated before, such differences may arise because actual net revenues differ from the original farmers' expectations. We attempt to minimise the chance of getting measurement errors by carefully accounting for annual expenses, especially the cost of capital and family labour. Under such circumstances, unexpected events within the agricultural year are more likely to cause the deviation of prices and of the levels of land attributes from their expected values.

To examine the consequences of such deviations, we estimate four Ricardian hedonic models using the same functional form as in the previous subsection. Tables 2.6 and 2.7 display the parameter estimates for both farms with at least one rented plot and farms with 100% rented land. The first thing to notice is the difference between R-squared values, higher values in the rental price equations. Such finding confirms the abovementioned hypothesis; the standard set of explanatory variables in the Ricardian models explains more of the variation in land (rental) prices than of the variation of annual net revenues. A pair wise comparison between coefficients associated to the same variable in both the net revenues and the rental price equations suggests that the selection of the land rents proxy matters. The F-test indicates that coefficients associated to temperature and rainfall are jointly different in the net revenues and rental price equations.[86] Moreover, the same test suggests that the size and sign of coefficients associated to the corresponding soil profiles and additional control variables are sensitive to the selection of the dependent variable.

[86] For farms with 100% rented land in the 2014 sample, the F-test suggests that such parameter estimates are jointly similar. However, none of the parameter estimates in the net revenues model is statistically significant, which drives the conclusion from the F-test.

# Figure 2.7 Rental prices and net revenues per hectare

**Figure 2.6a Net revenues and rental prices 2012**
**(farms with at least one rented plot)**

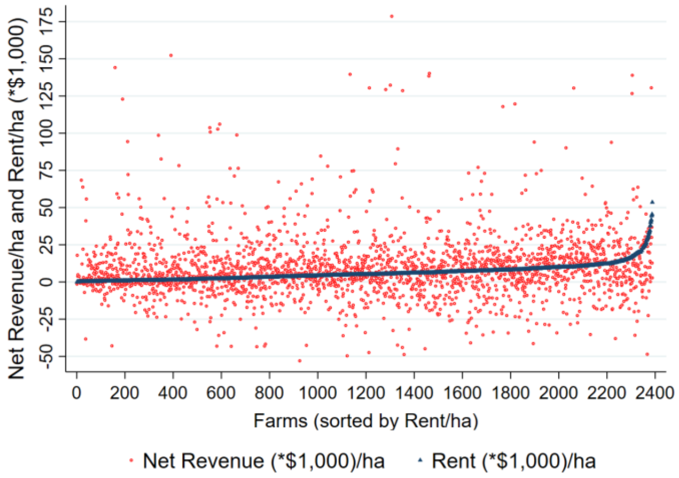



**Figure 2.6b Net revenues and rental prices 2012**
**(farms with 100% rented land)**

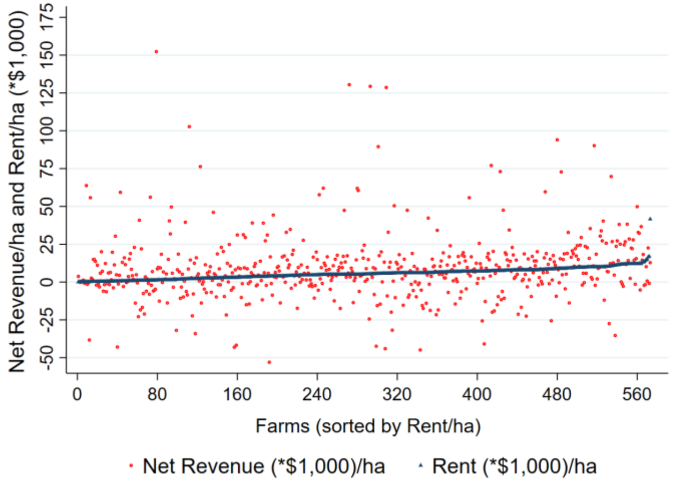



**Figure 2.7c Net revenues and rental prices gap 2012**
**(farms with at least one rented plot)**

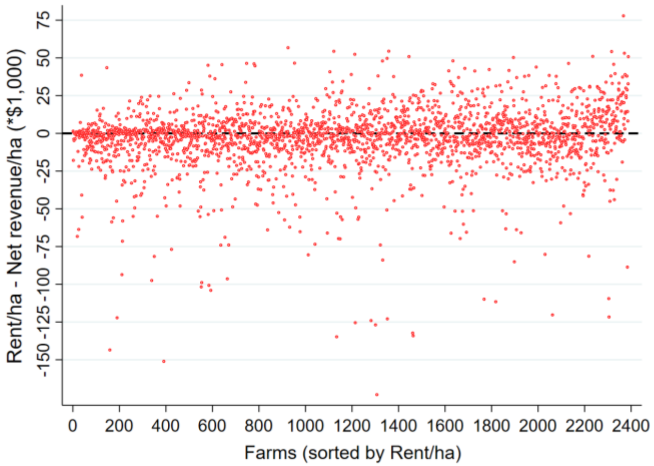



**Figure 2.7d Net revenues and rental prices gap 2012**
**(farms with 100% rented land)**

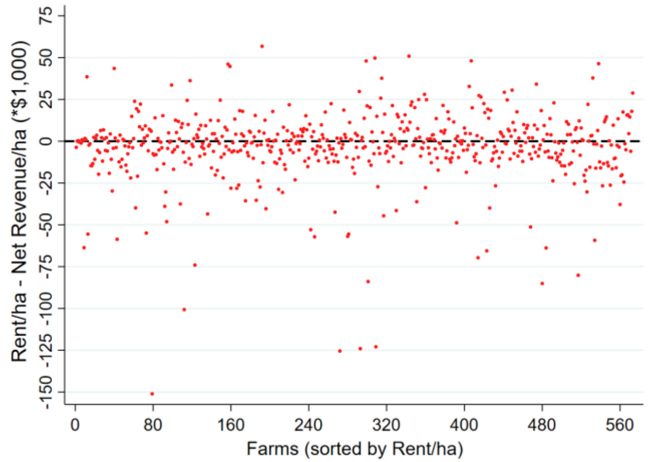
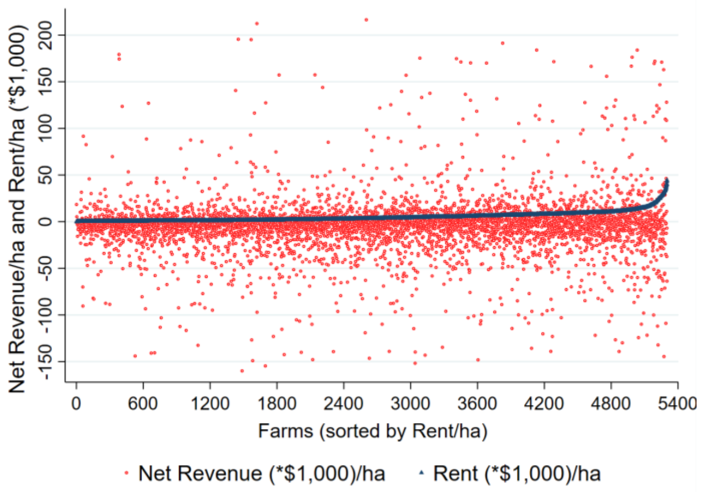



**Figure 2.7e Net revenues and rental prices 2014**
**(farms with at least one rented plot)**

**Figure 2.7f Net revenues and rental prices 2014**
**(farms with 100% rented land)**



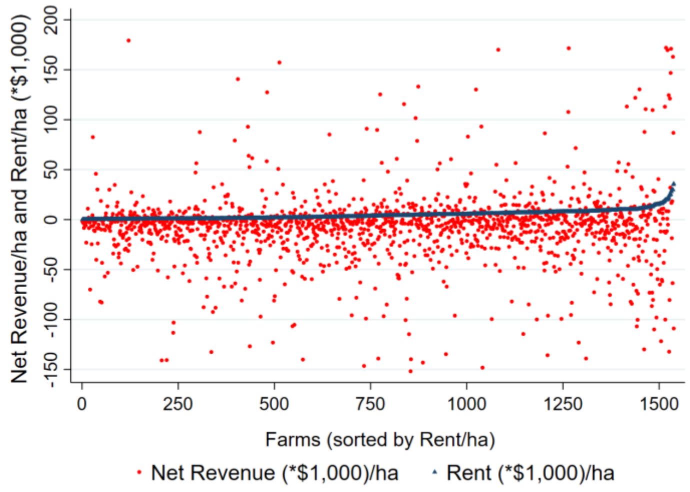
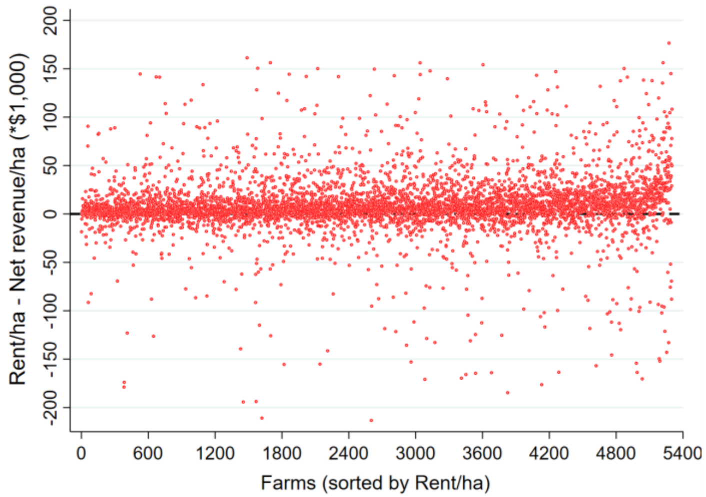
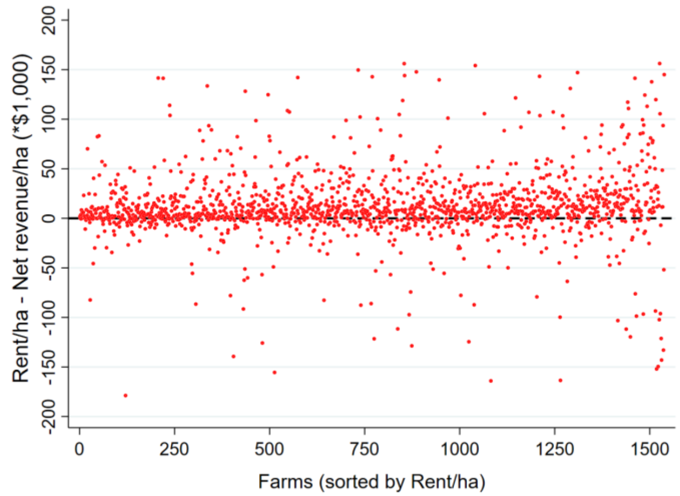




**Figure 2.7g Net revenues and rental prices gap 2014 (farms with at least one rented plot)**

**Figure 2.7h Net revenues and rental prices gap 2014 (farms with 100% rented land)**




Source: NAS (2012) and NAS (2014)

Looking at the estimated coefficients in the net revenues equation in Tables 2.4 and 2.6-2.7, we observe that some coefficients became insignificant. Comparing parameter estimates from the net revenues and rental prices equations, we encounter that some of the coefficients show different signs. Furthermore, the size of the majority of coefficients with the same sign in both equations is considerably larger in the net revenues equation than in the rental price equation. Thus, we believe that using net revenues in the Ricardian hedonic model may overestimate the size of implicit values of land attributes, especially climate attributes, as we noticed in previous studies (see for example Eid et al., 2007; Jain, 2007; Deressa and Hassan, 2009; Gebreegziabher et al., 2013).

**Table 2.6 Ricardian models: net revenues and rental prices**
**(Farms with at least one rented plot)**

| | 2012 | | | | 2014 | | | |
|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **Rent/ha** | **Chi2+** | **Chi2++** | **NetRev/ha** | **Rent/ha** | **Chi2+** | **Chi2++** |
| | (1) | (2) | [Prob>Chi2] | [Prob>Chi2] | (3) | (4) | [Prob>Chi2] | [Prob>Chi2] |
| | | | | **Climate** | | | | |
| *Temp. Sp-Su* | -1.1284*** | -0.1570*** | 6.45** | | 0.1777 | -0.1248*** | 1.59 | |
| | (0.3853) | (0.0506) | [0.01] | | (0.2403) | (0.0283) | [0.21] | |
| *Temp. Sp-Su sq.* | -0.1475** | -0.0069 | 5.67** | | -0.0055 | 0.0048 | 0.11 | |
| | (0.0593) | (0.0088) | [0.02] | | (0.0318) | (0.0037) | [0.75] | |
| *Temp. Au-Wi* | 1.0895*** | 0.1825*** | 5.23** | | 0.0296 | 0.1233*** | 0.13 | |
| | (0.3996) | (0.0515) | [0.02] | | (0.2603) | (0.0314) | [0.72] | |
| *Temp. Au-Wi sq.* | 0.1278*** | 0.0031 | 7.35*** | | 0.0347 | -0.0083** | 2.49 | |
| | (0.0464) | (0.0061) | [0.01] | | (0.0273) | (0.0032) | [0.11] | |
| *Rainfall Sp-Su* | -0.2594 | -0.0716 | 0.23 | | 0.0661 | -0.1412*** | 0.89 | |
| | (0.3929) | (0.0521) | [0.63] | 39.16*** | (0.2205) | (0.0248) | [0.35] | 29.69*** |
| *Rainfall Sp-Su sq.* | 0.0591 | 0.0151*** | 0.97 | [0.00] | -0.0188 | 0.0062*** | 3.71* | [0.00] |
| | (0.0449) | (0.0058) | [0.32] | | (0.0129) | (0.0018) | [0.05] | |
| *Rainfall Au-Wi* | 0.7110 | -0.1630* | 1.62 | | 0.1461 | 0.0779** | 0.05 | |
| | (0.6925) | (0.0873) | [0.20] | | (0.3196) | (0.0369) | [0.83] | |
| *Rainfall Au-Wi sq.* | -0.0402 | 0.0207 | 0.37 | | 0.0293 | -0.0048* | 2.94* | |
| | (0.1012) | (0.0128) | [0.54] | | (0.0198) | (0.0026) | [0.09] | |
| *Temp.*Rain. Sp-Su* | -0.0099 | -0.0269*** | 0.05 | | -0.0004 | -0.0127*** | 0.14 | |
| | (0.0735) | (0.0094) | [0.82] | | (0.0325) | (0.0040) | [0.70] | |
| *Temp.*Rain. Au-Wi* | -0.3865*** | -0.0054 | 11.67*** | | -0.0449 | 0.0179*** | 2.28 | |
| | (0.1119) | (0.0179) | [0.00] | | (0.0416) | (0.0051) | [0.13] | |
| | | | | **Other climate variables** | | | | |
| *Storms Sp-Su* | -0.0284 | 0.0216*** | 0.87 | | -0.0523 | -0.0027 | 1.61 | |
| | (0.0541) | (0.0069) | [0.35] | | (0.0391) | (0.0044) | [0.20] | |
| *Storms Au-Wi* | 0.0311 | -0.0330*** | 0.87 | | 0.1734*** | 0.0098 | 6.76*** | |
| | (0.0690) | (0.0108) | [0.35] | 1.45 | (0.0630) | (0.0071) | [0.01] | 11.24** |
| *Clouds Sp-Su* | 0.0277 | 0.0017 | 0.58 | [0.84] | 0.0259 | 0.0017 | 1.62 | [0.02] |
| | (0.0345) | (0.0042) | [0.45] | | (0.0190) | (0.0022) | [0.20] | |
| *Clouds Au-Wi* | -0.0311 | -0.0037 | 0.37 | | -0.0430* | -0.0003 | 3.05* | |
| | (0.0455) | (0.0054) | [0.54] | | (0.0244) | (0.0029) | [0.08] | |
| | | | | **Soils** | | | | |
| *Acrisol* | 0.0088 | 0.0025 | 0.03 | | 0.0181 | -0.0035** | 2.42 | |
| | (0.0365) | (0.0036) | [0.86] | | (0.0139) | (0.0016) | [0.12] | |
| *Andosol* | 0.0649* | -0.0009 | 3.47* | | -0.0174 | 0.0005 | 1.01 | |
| | (0.0352) | (0.0067) | [0.06] | | (0.0178) | (0.0020) | [0.31] | |
| *Arenosol* | | | | | -0.0199 | 0.0180*** | 3.95** | |
| | | | | | (0.0186) | (0.0047) | [0.05] | |
| *Cambisol* | 0.0115 | 0.0005 | 1.18 | | 0.0073 | 0.0001 | 1.17 | |
| | (0.0102) | (0.0011) | [0.28] | | (0.0067) | (0.0008) | [0.28] | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Castanozem* | -0.0370* | 0.0026 | 3.61* | | 0.0099 | 0.0049*** | 0.12 | |
| | (0.0210) | (0.0025) | [0.06] | | (0.0143) | (0.0014) | [0.73] | |
| *Chernozem* | -0.5227 | -0.5990*** | 0.01 | | -0.0526* | 0.0022 | 3.93** | |
| | (0.8290) | (0.0505) | [0.93] | | (0.0271) | (0.0063) | [0.05] | |
| *Feozem* | -0.0108 | -0.0028*** | 0.89 | | 0.0054 | -0.0012** | 1.64 | |
| | (0.0086) | (0.0010) | [0.35] | | (0.0052) | (0.0006) | [0.20] | |
| *Fluvisol* | 0.0297 | 0.0049** | e0.56 | | -0.0198 | 0.0012 | 0.39 | |
| | (0.0336) | (0.0021) | [0.45] | | (0.0338) | (0.0028) | [0.53] | |
| *Gleysol* | 0.1821** | -0.0056 | 7.01*** | | 0.0763** | -0.0082* | 7.03*** | |
| | (0.0717) | (0.0065) | [0.01] | 93.60*** | (0.0318) | (0.0047) | [0.01] | 99.16*** |
| *Litosol* | 0.0275 | -0.0016 | 2.14 | [0.00] | 0.0065 | 0.0002 | 0.29 | [0.00] |
| | (0.0200) | (0.0029) | [0.14] | | (0.0118) | (0.0013) | [0.59] | |
| *Luvisol* | 0.0066 | -0.0013 | 0.28 | | -0.0080 | -0.0002 | 0.61 | |
| | (0.0150) | (0.0016) | [0.59] | | (0.0100) | (0.0012) | [0.43] | |
| *Nitosol* | | | | | 0.0703*** | -0.0006 | 9.32*** | |
| | | | | | (0.0225) | (0.0063) | [0.00] | |
| *Planosol* | 0.0236* | -0.0007 | 3.71* | | -0.0133 | -0.0017* | 1.59 | |
| | (0.0127) | (0.0014) | [0.05] | | (0.0092) | (0.0010) | [0.21] | |
| *Ranker* | 9.9366*** | -0.4422 | 11.71*** | | 3.2713*** | -0.0587 | 33.44** | |
| | (3.0689) | (0.2796) | [0.00] | | (0.5491) | (0.1873) | [0.00] | |
| *Regosol* | -0.0044 | -0.0019* | 0.07 | | 0.0095* | -0.0010 | 3.32* | |
| | (0.0094) | (0.0011) | [0.79] | | (0.0057) | (0.0006) | [0.07] | |
| *Rendzina* | 0.0424** | -0.0015 | 4.79** | | 0.0372*** | -0.0037** | 11.20*** | |
| | (0.0201) | (0.0032) | [0.03] | | (0.0122) | (0.0015) | [0.00] | |
| *Solonchak* | 0.0106 | -0.0014 | 0.89 | | -0.0151 | -0.0004 | 1.60 | |
| | (0.0129) | (0.0014) | [0.34] | | (0.0116) | (0.0012) | [0.21] | |
| *Solonetz* | 1.9126*** | -0.0910** | 31.82*** | | 0.2351** | 0.0167 | 4.97** | |
| | (0.3584) | (0.0424) | [0.00] | | (0.0981) | (0.0108) | [0.03] | |
| *Xerosol* | 0.0323*** | 0.0002 | 20.55*** | | 0.0002 | 0.0016*** | 0.07 | |
| | (0.0072) | (0.0008) | [0.00] | | (0.0057) | (0.0006) | [0.80] | |
| *Yermosol* | 0.0321 | -0.0069*** | 3.28* | | -0.0188 | -0.0027* | 1.17 | |
| | (0.0218) | (0.0021) | [0.07] | | (0.0149) | (0.0014) | [0.28] | |
| | | | | **Control variables** | | | | |
| *Area*1,000* | 3.8448*** | -1.3979*** | 34.30*** | | 7.8979*** | -0.8468*** | 74.13*** | |
| | (0.8892) | (0.1909) | [0.00] | | (1.0121) | (0.1503) | [0.00] | |
| *Area*1,000 sq.* | -0.8272*** | 0.3178*** | 27.43*** | | -1.5515*** | 0.1109*** | 27.69*** | |
| | (0.2130) | (0.0629) | [0.00] | | (0.3167) | (0.0312) | [0.00] | |
| *City* | -0.0305 | 0.0043 | 1.23 | | 0.0459** | -0.0051** | 7.55*** | |
| | (0.0317) | (0.0037) | [0.27] | | (0.0185) | (0.0023) | [0.01] | |
| *Water body* | -0.0289* | -0.0031* | 3.02* | | 0.0032 | -0.0005 | 0.18 | |
| | (0.0150) | (0.0017) | [0.08] | | (0.0088) | (0.0010) | [0.67] | |
| *River* | -0.0102 | -0.0017 | 0.43 | 57.54*** | -0.0157* | -0.0045*** | 1.55 | 148.61*** |
| | (0.0131) | (0.0015) | [0.51] | [0.00] | (0.0091) | (0.0010) | [0.21] | [0.00] |
| *Road density* | 0.0010 | 0.0002 | 0.26 | | -0.0002 | 0.0004*** | 0.59 | |
| | (0.0016) | (0.0002) | [0.61] | | (0.0008) | (0.0001) | [0.44] | |
| *Irrigation* | 0.0211*** | 0.0083*** | 3.82* | | 0.0199*** | 0.0093*** | 7.83*** | |
| | (0.0066) | (0.0008) | [0.05] | | (0.0038) | (0.0004) | [0.00] | |
| *Ejidal* | -0.0035 | 0.0011** | 1.28 | | -0.0073** | 0.0006* | 7.50*** | |
| | (0.0040) | (0.0005) | [0.26] | | (0.0029) | (0.0003) | [0.00] | |
| *Electricity* | 0.4140 | 0.1088** | 0.63 | | 0.9023*** | 0.2300*** | 4.50** | |
| | (0.3880) | (0.0440) | [0.43] | | (0.3174) | (0.0343) | [0.03] | |
| Constant | 7.2419*** | 7.6005*** | | | -1.5034 | 7.3147*** | | |
| | (2.2420) | (0.2535) | | | (1.0543) | (0.1308) | | |
| Farm types (FE) | YES | YES | | | YES | YES | | |
| States (FE) | YES | YES | | | YES | YES | | |
| Observations | 2,388 | 2,388 | | | 5,301 | 5,301 | | |
| R-squared | 0.108 | 0.401 | | | 0.093 | 0.418 | | |

[+] Null hypothesis: not difference between individual coefficients
[++] Null hypothesis: not difference between group of coefficients
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# Table 2.7 Ricardian models: net revenues and rental prices
## (Farms with 100% rented land)

| | 2012 | | | | 2014 | | | |
|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **Rent/ha** | **Chi2+** | **Chi2++** | **NetRev/ha** | **Rent/ha** | **Chi2+** | **Chi2++** |
| | (1) | (2) | [Prob>Chi2] | [Prob>Chi2] | (3) | (4) | [Prob>Chi2] | [Prob>Chi2] |
| | | | | **Climate** | | | | |
| *Temp. Sp-Su* | -2.7021*** | -0.1843* | 7.99*** | | -0.4736 | -0.1387** | 0.53 | |
| | (0.9417) | (0.1037) | [0.00] | | (0.4703) | (0.0543) | [0.47] | |
| *Temp. Sp-Su sq.* | -0.2773 | -0.0211 | 2.52 | | 0.0198 | 0.0028 | 0.08 | |
| | (0.1708) | (0.0184) | [0.11] | | (0.0631) | (0.0074) | [0.78] | |
| *Temp. Au-Wi* | 2.2762** | 0.2098** | 5.18** | | 0.7689 | 0.1241** | 1.68 | |
| | (0.9601) | (0.1061) | [0.02] | | (0.5068) | (0.0593) | [0.20] | |
| *Temp. Au-Wi sq.* | 0.2255* | 0.0145 | 3.10* | | -0.0204 | -0.0074 | 0.06 | |
| | (0.1268) | (0.0138) | [0.08] | | (0.0531) | (0.0062) | [0.80] | |
| *Rainfall Sp-Su* | -0.2140 | 0.0823 | 0.07 | | 0.5305 | -0.1430*** | 2.47 | |
| | (1.1611) | (0.1222) | [0.79] | 32.00*** | (0.4362) | (0.0472) | [0.12] | 10.87 |
| *Rainfall Sp-Su sq.* | 0.2418** | 0.0047 | 6.01** | [0.00] | -0.0283 | 0.0074** | 1.80 | [0.37] |
| | (0.1022) | (0.0114) | [0.01] | | (0.0271) | (0.0030) | [0.18] | |
| *Rainfall Au-Wi* | -0.4056 | -0.4433** | 0.00 | | -0.4670 | 0.1321** | 0.99 | |
| | (2.0004) | (0.2011) | [0.98] | | (0.6125) | (0.0667) | [0.32] | |
| *Rainfall Au-Wi sq.* | 0.3340 | 0.0480* | 1.62 | | 0.0471 | -0.0103** | 1.74 | |
| | (0.2379) | (0.0248) | [0.20] | | (0.0442) | (0.0052) | [0.19] | |
| *Temp.*Rain. Sp-Su* | 0.2077 | -0.0412* | 1.49 | | -0.0747 | -0.0150** | 0.94 | |
| | (0.2159) | (0.0222) | [0.22] | | (0.0625) | (0.0070) | [0.33] | |
| *Temp.*Rain. Au-Wi* | -1.5017*** | -0.0914* | 8.53*** | | 0.0470 | 0.0097 | 0.32 | |
| | (0.5105) | (0.0552) | [0.00] | | (0.0672) | (0.0081) | [0.57] | |
| | | | | **Other climate variables** | | | | |
| *Storms Sp-Su* | -0.1822 | 0.0005 | 2.30 | | 0.0240 | 0.0073 | 0.01 | |
| | (0.1437) | (0.0712) | [0.13] | | (0.0165) | (0.0072) | [0.92] | |
| *Storms Au-Wi* | 0.0340 | 0.1224 | 0.11 | | -0.0507* | -0.0055 | 1.19 | |
| | (0.2688) | (0.1198) | [0.74] | 3.62 | (0.0293) | (0.0103) | [0.28] | 3.22 |
| *Clouds Sp-Su* | -0.0204 | 0.0241 | 0.03 | [0.46] | -0.0061 | -0.0017 | 0.51 | [0.52] |
| | (0.0822) | (0.0367) | [0.85] | | (0.0078) | (0.0039) | [0.47] | |
| *Clouds Au-Wi* | 0.0485 | -0.0252 | 0.17 | | 0.0044 | 0.0062 | 0.48 | |
| | (0.1142) | (0.0462) | [0.68] | | (0.0100) | (0.0049) | [0.49] | |
| | | | | **Soils** | | | | |
| *Acrisol* | 0.0927 | -0.0169* | 2.72* | | 0.0313 | -0.0052** | 2.05 | |
| | (0.0702) | (0.0088) | [0.10] | | (0.0260) | (0.0026) | [0.15] | |
| *Andosol* | 0.0348 | -0.0057 | 0.24 | | 0.0043 | -0.0013 | 0.04 | |
| | (0.0877) | (0.0137) | [0.63] | | (0.0294) | (0.0029) | [0.85] | |
| *Cambisol* | 0.0321 | 0.0020 | 1.72 | | 0.0141 | -0.0012 | 1.60 | |
| | (0.0243) | (0.0025) | [0.19] | | (0.0123) | (0.0013) | [0.21] | |
| *Castanozem* | 0.1426*** | -0.0000 | 16.57*** | | -0.0258 | 0.0032 | 1.35 | |
| | (0.0369) | (0.0050) | [0.00] | | (0.0255) | (0.0028) | [0.25] | |
| *Feozem* | -0.0117 | 0.0006 | 0.32 | | 0.0106 | 0.0000 | 1.34 | |
| | (0.0228) | (0.0025) | [0.57] | | (0.0093) | (0.0010) | [0.25] | |
| *Fluvisol* | -0.0023 | 0.0017 | 0.01 | | 0.0033 | 0.0034 | 0.00 | |
| | (0.0554) | (0.0047) | [0.94] | | (0.0523) | (0.0034) | [0.99] | |
| *Gleysol* | 0.4809*** | 0.0280** | 14.59*** | | 0.1161** | -0.0156*** | 7.83*** | |
| | (0.1254) | (0.0137) | [0.00] | 78.07*** | (0.0481) | (0.0038) | [0.01] | 78.06*** |
| *Litosol* | 0.1479*** | 0.0049 | 10.57*** | [0.00] | 0.0017 | -0.0012 | 0.02 | [0.00] |
| | (0.0465) | (0.0051) | [0.00] | | (0.0221) | (0.0022) | [0.89] | |
| *Luvisol* | -0.0086 | -0.0006 | 0.07 | | 0.0118 | -0.0011 | 0.48 | |
| | (0.0308) | (0.0030) | [0.78] | | (0.0190) | (0.0022) | [0.49] | |
| *Planosol* | 0.0180 | 0.0013 | 0.20 | | -0.0292* | -0.0044** | 2.26 | |
| | (0.0390) | (0.0033) | [0.65] | | (0.0168) | (0.0020) | [0.13] | |
| *Regosol* | -0.0023 | 0.0002 | 0.01 | | 0.0151 | -0.0011 | 2.32 | |
| | (0.0220) | (0.0021) | [0.91] | | (0.0108) | (0.0011) | [0.13] | |
| *Rendzina* | 0.1448** | -0.0324*** | 8.17*** | | 0.0535** | -0.0045 | 5.01** | |
| | (0.0654) | (0.0081) | [0.00] | | (0.0264) | (0.0028) | [0.03] | |
| *Solonchak* | -0.0237 | -0.0012 | 0.68 | | -0.0382* | -0.0017 | 3.32* | |
| | (0.0289) | (0.0025) | [0.41] | | (0.0204) | (0.0022) | [0.07] | |
| *Solonetz* | 0.6839 | -0.0405 | 1.15 | | 0.2872*** | 0.0196*** | 37.87*** | |
| | (0.7154) | (0.0704) | [0.28] | | (0.0443) | (0.0046) | [0.00] | |
| *Xerosol* | 0.0284* | 0.0007 | 3.70* | | 0.0081 | 0.0015 | 0.43 | |
| | (0.0152) | (0.0017) | [0.05] | | (0.0102) | (0.0011) | [0.51] | |
| *Yermosol* | -0.0158 | -0.0029 | 0.09 | | 0.0226 | -0.0015 | 0.76 | |
| | (0.0451) | (0.0037) | [0.76] | | (0.0282) | (0.0020) | [0.38] | |
| | | | | **Control variables** | | | | |
| *Area*1,000* | 13.2376*** | -0.3332 | 41.16*** | | 11.7210*** | -0.6935*** | 20.89*** | |
| | (2.2308) | (0.2927) | [0.00] | | (2.7712) | (0.2500) | [0.00] | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Area*1,000 sq.* | -4.6116*** | 0.0029 | 28.47*** | | -1.8179*** | 0.0722** | 24.44*** | |
| | (0.9136) | (0.1074) | [0.00] | | (0.3901) | (0.0354) | [0.00] | |
| *City* | -0.0468 | -0.0046 | 0.43 | | 0.0881** | -0.0064* | 6.97*** | |
| | (0.0685) | (0.0069) | [0.51] | | (0.0365) | (0.0038) | [0.01] | |
| *Water body* | -0.0522 | -0.0006 | 2.46 | | -0.0163 | 0.0003 | 1.17 | |
| | (0.0348) | (0.0037) | [0.12] | | (0.0156) | (0.0017) | [0.28] | |
| *River* | 0.0126 | -0.0004 | 0.24 | 51.47*** | 0.0050 | -0.0058*** | 0.33 | 61.47*** |
| | (0.0279) | (0.0030) | [0.62] | [0.00] | (0.0191) | (0.0019) | [0.57] | [0.00] |
| *Road density* | -0.0060 | 0.0000 | 2.39 | | -0.0002 | 0.0003* | 0.09 | |
| | (0.0042) | (0.0004) | [0.12] | | (0.0015) | (0.0002) | [0.77] | |
| *Irrigation* | 0.0690*** | 0.0151*** | 7.07*** | | 0.0121* | 0.0095*** | 0.14 | |
| | (0.0214) | (0.0028) | [0.01] | | (0.0071) | (0.0008) | [0.71] | |
| *Ejidal* | -0.0015 | 0.0012 | 0.13 | | -0.0027 | 0.0017*** | 0.78 | |
| | (0.0080) | (0.0008) | [0.72] | | (0.0051) | (0.0005) | [0.38] | |
| *Electricity* | -1.6371* | 0.0667 | 3.63* | | 1.6822** | 0.1685** | 4.46** | |
| | (0.9472) | (0.0907) | [0.06] | | (0.7303) | (0.0723) | [0.03] | |
| Constant | 14.1020*** | 8.1377*** | | | 0.6474 | 7.2227*** | | |
| | (4.5794) | (0.5945) | | | (2.2805) | (0.2286) | | |
| Farm types (FE) | YES | YES | | | YES | YES | | |
| States (FE) | YES | YES | | | YES | YES | | |
| Observations | 573 | 573 | | | 1,538 | 1,538 | | |
| R-squared | 0.234 | 0.509 | | | 0.111 | 0.490 | | |

+ Null hypothesis: not difference between individual coefficients
++ Null hypothesis: not difference between group of coefficients
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Using data on the same farms and holding other explanatory variables at means, Tables 2.8 and 2.9 show the marginal effects of the six-monthly temperature and rainfall on net revenues and rental prices. According to these results, a warmer spring-summer (autumn-winter) season would shrink (rise) net revenues and land rental prices. We do not find a significant marginal effect of rainfall on net revenues. For rental prices, additional rainfall in the spring-summer season reduces land rents while the effect of extra rainfall in the autumn and winter season is ambiguous since the direction of such effect changes among the 2012 and 2014 samples. Although individual tests suggests that not all of the marginal effects are statistically different,[87] the F-test concludes that we fail to reject the alternative hypothesis of systematic differences between all marginal effects of climate variables from the net revenue and land rental price hedonic models.[88]

[87] The conclusion of the F-test relies on the size of the standard errors. For some of the coefficients with remarkably large standard errors, the F-test concludes that there are not systematic differences in the pair wise comparison, however, this conclusion might be taken with caution since most of the coefficients in the net revenues equation are not statistically different from zero at the 10% significance level.

[88] For farms with 100% rented land in the 2014 sample, the F-test suggests that implicit prices are jointly similar. However, none of the implicit prices from the net revenues model is statistically significant, which drives the conclusion from the F-test.

**Table 2.8 Ricardian models: marginal effects (farms with at least one rented plot)**

| | 2012 | | | 2014 | | |
|---|---|---|---|---|---|---|
| | **NetRev/ha** | **Rent/ha** | **Chi2+** | **NetRev/ha** | **Rent/ha** | **Chi2+** |
| **VARIABLES** | (1) | (2) | [Prob>Chi2] | (3) | (4) | [Prob>Chi2] |
| | | **Climate** | | | | |
| *Temperature Sp-Su* | -1.1284*** | -0.1570*** | 6.45** | 0.1777 | -0.1248*** | 1.59 |
| | (0.3853) | (0.0506) | [0.01] | (0.2403) | (0.0283) | [0.21] |
| *Temperature Au-Wi* | 1.0895*** | 0.1825*** | 5.23** | 0.0296 | 0.1233*** | 0.13 |
| | (0.3996) | (0.0515) | [0.02] | (0.2603) | (0.0314) | [0.72] |
| *Rainfall Sp-Su* | -0.2594 | -0.0716 | 0.23 | 0.0661 | -0.1412*** | 0.89 |
| | (0.3929) | (0.0521) | [0.63] | (0.2205) | (0.0248) | [0.35] |
| *Rainfall Au-Wi* | 0.7110 | -0.1630* | 1.62 | 0.1461 | 0.0779** | 0.05 |
| | (0.6925) | (0.0873) | [0.20] | (0.3196) | (0.0369) | [0.83] |
| F-test: | | | | | | |
| Marginal effects are equal | | 13.86*** | | | 8.90* | |
| Prob > F | | [0.01] | | | [0.06] | |
| Farm types (FE) | YES | YES | | YES | YES | |
| States (FE) | YES | YES | | YES | YES | |
| Observations | 2,388 | 2,388 | | 5,301 | 5,301 | |

+ Null hypothesis: not difference between individual marginal effects
Small: farms with less than 20 hectares of land; large: farms with 20 or more than 20 hectares; irrigated: farms with some of their land with an irrigation system; rain-fed: none of the agricultural fields has an irrigation system; ejidal: some land in these farms is under the ejido's land tenure regime. FE: fixed effects.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 2.9 Ricardian models: marginal effects (farms with 100% rented land)**

| | 2012 | | | 2014 | | |
|---|---|---|---|---|---|---|
| | **NetRev/ha** | **Rent/ha** | **Chi2+** | **NetRev/ha** | **Rent/ha** | **Chi2+** |
| **VARIABLES** | (1) | (2) | [Prob>Chi2] | (3) | (4) | [Prob>Chi2] |
| | | **Climate** | | | | |
| *Temperature Sp-Su* | -2.7021*** | -0.1843* | 7.99*** | -0.4736 | -0.1387** | 0.53 |
| | (0.9417) | (0.1037) | [0.00] | (0.4703) | (0.0543) | [0.47] |
| *Temperature Au-Wi* | 2.2762** | 0.2098** | 5.18** | 0.7689 | 0.1241** | 1.68 |
| | (0.9601) | (0.1061) | [0.02] | (0.5068) | (0.0593) | [0.20] |
| *Rainfall Sp-Su* | -0.2140 | 0.0823 | 0.07 | 0.5305 | -0.1430*** | 2.47 |
| | (1.1611) | (0.1222) | [0.79] | (0.4362) | (0.0472) | [0.12] |
| *Rainfall Au-Wi* | -0.4056 | -0.4433** | 0.00 | -0.4670 | 0.1321** | 0.99 |
| | (2.0004) | (0.2011) | [0.98] | (0.6125) | (0.0667) | [0.32] |
| F-test (Marginal effects are equal) | | 8.52* | | | 7.26 | |
| Prob > F | | [0.07] | | | [0.12] | |
| Farm types (FE) | YES | YES | | YES | YES | |
| States (FE) | YES | YES | | YES | YES | |
| Observations | 573 | 573 | | 1,538 | 1,538 | |

+ Null hypothesis: not difference between individual marginal effects
Small: farms with less than 20 hectares of land; large: farms with 20 or more than 20 hectares; irrigated: farms with some of their land with an irrigation system; rain-fed: none of the agricultural fields has an irrigation system; ejidal: some land in these farms is under the ejido's land tenure regime. FE: fixed effects.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, implicit values of land attributes associated to climate variables differ not only in size but also in their signs when we use net revenues or rental prices as indicators of land rents. To examine the implications of such differences, we assess the potential impact of climate change on net revenues and land rental prices using the parameter estimates in Tables 2.6-2.7 and predictions about future climate from three different GCMs. Thus, the following subsection presents the results of such speculations.

### *2.4.3. The effects of climate change on net revenues and land rental prices*

To assess the effect of climate change on agriculture we combine information from the set of Ricardian hedonic models with predictions about changes on climate from three GCMs.[89] The set of GCMs comprise the Community Climate System Model 4.0 (CCSM4.0), Model for Interdisciplinary Research In Climate 5 (MIROC5), and Meteorological Research Institute Coupled General Circulation Model 3 (MRI-CGCM3) models. To provide an extensive overview of the effects of climate change on agriculture, we use the predictions from the abovementioned GCMs for each Representative Concentration Pathway (RCP) in the Fifth Assessment Intergovernmental Panel on Climate Change (IPCC) report (IPCC, 2013).[90] Similar to current climate data, Hijmans et al. (2005) downscaled data from the CCSM4.0, MIROC5 and MRI-CGCM3 models and released a GIS-database for future climate (raster database with ~1km$^2$ at the Equator).

Using the Control Areas' (CAs) location codes we assign the predictions for average temperature and rainfall in the 2041-2060 period to the corresponding plots. Then, we transform plot-level to farm-level values using the weighted average of such values as for current climate in subsection 2.3.3.2. Unfortunately, Hijmans et al only provide data on annual changes of temperature; therefore, we have to assume the same change in both seasons. Tables 2.10 and 2.11 (2.12 and 2.13) show that farms with at least one rented plot (with 100% rented land) in

[89] We choose these GCMs based on Hidalgo and Alfaro (2014) and data availability in the Worldclim database.
[90] RCPs represent four greenhouse gas concentration paths in the IPCC report. RCPs do no refer to emissions.

the 2012 and 2014 samples respectively, will face a warmer future in which temperature would rise between 0.81ºC and 3.29ºC (0.81ºC and 3.16ºC). Regarding rainfall, the GCMs predict that some farms would face a drier future while other farms would face a wetter environment. Tables 2.10 and 2.11 (2.12 and 2.13) suggests that the change in the level of rainfall is expected to vary between -395 mm and 224 mm (-357 mm and 200 mm). Tables 2.10-2.13 also show the average change of temperature and rainfall in the corresponding farms under different scenarios.

To obtain the percentage change in net revenues and rental prices per hectare of individual farms, we use the set of coefficients in Tables 2.6-2.7 and the following formula: $\Delta\ln[\pi_i^a] = \Delta F_i = [\hat{F}_{i,2041-2060} - F_{i,2012}]$ or $\Delta\ln[R_i] = \Delta F_i = [\hat{F}_{i,2041-2060} - F_{i,2012}]$, where $\hat{F}_i$ and $F_i$are the predicted and current climate values for the $i$-th farm. Tables 2.10-2.13 show that estimates of the capitalisation of climate change on land rents from the net revenues and rental prices equations are radically different.

For the 2012 sample, the net revenues model predicts average losses between -14.78% and -3.09% of the current net revenue per hectare (between -106.77% and +4.43% in farms with 100% rented land). Conversely, the rental price model predicts average benefits between +4.03% and +13.12% of the current rental price per hectare (between +3.21% and +21.83% in farms with 100% rented land). Regarding the 2014 sample, the net revenues model predicts large average benefits for those farms in the sample, varying between +24.22% and +67.46% (between +28.26% and +68.87% in farms with 100% rented land). The rental price models identify changes between -1.85% and +1.43% with respect to current rental prices per hectare (between -4.10% and -0.87% in farms with 100% rented land).

## Table 2.10 Capitalisation of climate change 2012 (farms with at least one rented plot)

| | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Net Rev/ha*** | **Rent/ha*** | **Net Rev/ha*** | **Rent/ha*** | **Net Rev/ha*** | **Rent/ha*** | **Net Rev/ha*** | **Rent/ha*** |
| | | | | | **2012** | | | | |
| | **Δ Net Rev/ha (%)** | **-6.90** | **4.03** | **-8.21** | **7.41** | **-9.46** | **4.63** | **-9.14** | **10.58** |
| | **Range [min-max]** | **[-11.81-23.13]** | **[0.10-38.19]** | **[-16.39-38.03]** | **[2.55-48.42]** | **[-16.46-22.23]** | **[-3.60-39.01]** | **[-25.36-79.35]** | **[3.44-80.87]** |
| | Δ Net Rev/ha ($/ha) | -1,022 | 208 | -1,202 | 413 | -1,446 | 258 | -1,360 | 591 |
| | Range [min-max] | [-16279-4035] | [0-4490] | [-21441-9752] | [2-6794] | [-23222-9212] | [-70-7025] | [-33160-22520] | [2-8115] |
| **CCSM4** | Δ Net Rev ($*million) | -309 | 54 | -401 | 112 | -419 | 71 | -490 | 158 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.28 [0.99-1.55] | | 1.74 [1.41-2.17] | | 1.55 [1.27-1.96] | | 2.36 [1.82-2.93] | |
| | Δ Temp. auwi (ºC) | 1.28 [0.99-1.55] | | 1.74 [1.41-2.17] | | 1.55 [1.27-1.96] | | 2.36 [1.82-2.93] | |
| | Δ Rain. spsu (mm) | -7 [-120-+12] | | -18 [-145-+3] | | -7 [-110-+267] | | -26 [-190-+2] | |
| | Δ Rain. auwi (mm) | -4 [-122-+10] | | -11 [-147-+2] | | -4 [-119-+223] | | -17 [-221-+1] | |
| | **Δ Net Rev/ha (%)** | **-10.36** | **4.09** | **-11.97** | **6.16** | **-6.64** | **9.19** | **-14.78** | **7.61** |
| | **Range [min-max]** | **[-26.48-37.99]** | **[-8.72-48.03]** | **[-30.87-53.32]** | **[-6.30-49.68]** | **[-19.25-24.26]** | **[-5.67-30.48]** | **[-40.79-48.99]** | **[-16.86-42.99]** |
| | Δ Net Rev/ha ($/ha) | -1,546 | 221 | -1,558 | 319 | -953 | 544 | -2,074 | 420 |
| | Range [min-max] | [-19026-13580] | [-221-3886] | [-26260-32181] | [-550-9830] | [-17124-10980] | [-309-6543] | [-33015-29333] | [-1324-7700] |
| **MIROC5** | Δ Net Rev ($*million) | -470 | 73 | -598 | 82 | -334 | 164 | -703 | 122 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.60 [1.28-2.16] | | 2.04 [1.58-2.69] | | 1.85 [1.29-2.54] | | 2.48 [1.88-3.16] | |
| | Δ Temp. auwi (ºC) | 1.60 [1.28-2.16] | | 2.04 [1.58-2.69] | | 1.85 [1.29-2.54] | | 2.48 [1.88-3.16] | |
| | Δ Rain. spsu (mm) | -4 [-161-+55] | | -12 [-172-+48] | | -23 [-102-+49] | | -14 [-142-+100] | |
| | Δ Rain. auwi (mm) | -3 [-110-+38] | | -5 [-105-+31] | | -16 [-65-+27] | | -9 [-87-+59] | |
| | **Δ Net Rev/ha (%)** | **-4.14** | **4.12** | **-5.72** | **7.08** | **-6.87** | **4.09** | **-3.09** | **13.12** |
| | **Range [min-max]** | **[-16.01-16.98]** | **[-13.54-34.38]** | **[-18.79-16.20]** | **[-24.51-32.1]** | **[-19.70-16.10]** | **[-25.69-29.31]** | **[-45.89-58.39]** | **[-27.85-53.99]** |
| | Δ Net Rev/ha ($/ha) | -623 | 192 | -891 | 429 | -1,098 | 265 | -557 | 844 |
| | Range [min-max] | [-16120-15461] | [-3031-10430] | [-22466-16096] | [-3349-9947] | [-24481-6439] | [-4085-7284] | [-33044-46263] | [-1898-14359] |
| **MRI-CGCM3** | Δ Net Rev ($*million) | -197 | 43 | -272 | 126 | -302 | 79 | -176 | 233 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.04 [0.82-1.69] | | 1.32 [1.07-1.69] | | 1.27 [0.83-1.69] | | 1.93 [1.26-2.82] | |
| | Δ Temp. auwi (ºC) | 1.04 [0.82-1.69] | | 1.32 [1.07-1.69] | | 1.27 [0.83-1.69] | | 1.93 [1.26-2.82] | |
| | Δ Rain. spsu (mm) | -9 [-111-+88] | | -18 [-127-+145] | | -5 [-116-+169] | | -36 [-193-+160] | |
| | Δ Rain. auwi (mm) | -4 [-111-+51] | | -13 [-75-+110] | | -4 [-69-+116] | | -26 [-105-+112] | |

Minimum and maximum values of the corresponding distributions in brackets
These figures correspond to the average losses/gains of the farms in the corresponding samples

## Table 2.11 Capitalisation of climate change 2014 (farms with at least one rented plot)

| | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
|---|---|---|---|---|---|---|---|---|---|
| | | **NetRev/ha*** | **Rent/ha*** | **NetRev/ha*** | **Rent/ha*** | **NetRev/ha*** | **Rent/ha*** | **NetRev/ha*** | **Rent/ha*** |
| | | | | | **2014** | | | | |
| **CCSM4** | **Δ Net Rev/ha (%)** | **31.03** | **0.77** | **43.58** | **1.18** | **39.89** | **-0.18** | **63.68** | **1.43** |
| | **Range [min-max]** | **[9.49-38.55]** | **[-2.85-21.2]** | **[19.67-58.06]** | **[-4.47-25.22]** | **[20.12-51.58]** | **[-4.17-19.53]** | **[30.26-83.29]** | **[-8.87-31.51]** |
| | Δ Net Rev/ha ($/ha) | 5,204 | 20 | 7,273 | 36 | 6,759 | -16 | 10,619 | 38 |
| | Range [min-max] | [0-68520] | [-911-1903] | [0-97112] | [-699-2638] | [0-100741] | [-974-2791] | [0-137996] | [-979-2718] |
| | Δ Net Rev ($*million) | 2,271 | -6 | 3,202 | -6 | 2,827 | -14 | 4,544 | -13 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.33 [0.98-1.55] | | 1.78 [1.42-2.17] | | 1.61 [1.27-1.96] | | 2.41 [1.82-2.93] | |
| | Δ Temp. auwi (ºC) | 1.33 [0.98-1.55] | | 1.78 [1.42-2.17] | | 1.61 [1.27-1.96] | | 2.41 [1.82-2.93] | |
| | Δ Rain. spsu (mm) | -15 [-194-+14] | | -25 [-228-+0.23] | | -10 [-182-+34] | | -36 [-285-+3] | |
| | Δ Rain. auwi (mm) | -8 [-215-+10] | | -14 [-270-+015] | | -6 [-211-+22] | | -21 [-395-+2] | |
| **MIROC5** | **Δ Net Rev/ha (%)** | **40.15** | **-0.33** | **51.92** | **1.38** | **45.09** | **1.17** | **67.46** | **0.10** |
| | **Range [min-max]** | **[11.07-59.75]** | **[-13.88-22.48]** | **[7.94-79.9]** | **[-15.89-36.49]** | **[15.47-68.39]** | **[-20.59-22.01]** | **[34.76-99.02]** | **[-21.41-30.00]** |
| | Δ Net Rev/ha ($/ha) | 6,490 | -29 | 8,228 | 41 | 7,154 | 36 | 10,814 | -16 |
| | Range [min-max] | [0-83039] | [-938-2088] | [0-112810] | [-1198-5301] | [0-95186] | [-1811-2476] | [0-141891] | [-1625-3313] |
| | Δ Net Rev ($*million) | 3,018 | -26 | 3,963 | -29 | 3,315 | -7 | 5,014 | -45 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.61 [1.22-2.18] | | 2.04 [1.51-2.79] | | 1.83 [1.25-2.65] | | 2.48 [1.84-3.29] | |
| | Δ Temp. auwi (ºC) | 1.61 [1.22-2.18] | | 2.04 [1.51-2.79] | | 1.83 [1.25-2.65] | | 2.48 [1.84-3.29] | |
| | Δ Rain. spsu (mm) | -9 [-233-+134] | | -28 [-357-+150] | | -27 [-230-+208] | | -24 [-308-+204] | |
| | Δ Rain. auwi (mm) | -6 [-152-+69] | | -14 [-233-+78] | | -17 [-150-+108] | | -14 [-201-+119] | |
| **MRI-CGCM3** | **Δ Net Rev/ha (%)** | **24.22** | **0.84** | **31.44** | **-0.34** | **31.65** | **-1.85** | **48.89** | **0.25** |
| | **Range [min-max]** | **[9.94-36.73]** | **[-8.6-24.21]** | **[16.66-49.29]** | **[-17.7-19.59]** | **[13.47-56.45]** | **[-18.55-16.32]** | **[26.1-81.57]** | **[-16.84-26.89]** |
| | Δ Net Rev/ha ($/ha) | 3,989 | 38 | 5,224 | -6 | 5,308 | -64 | 8,138 | 33 |
| | Range [min-max] | [0-55311] | [-1196-3205] | [0-75306] | [-3491-3079] | [0-75235] | [-4083-2062] | [0-125897] | [-3072-5221] |
| | Δ Net Rev ($*million) | 1,697 | -2 | 2,140 | 1 | 2,106 | -16 | 3,135 | 17 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.08 [ 0.81-2.11] | | 1.32 [0.99-1.89] | | 1.26 [0.83-1.77] | | 1.94 [1.11-3.10] | |
| | Δ Temp. auwi (ºC) | 1.08 [ 0.81-2.11] | | 1.32 [0.99-1.89] | | 1.26 [0.83-1.77] | | 1.94 [1.11-3.10] | |
| | Δ Rain. spsu (mm) | -13 [-292-+87] | | -6 [-242-+212] | | 10 [-178-+224] | | -21 [-342-+140] | |
| | Δ Rain. auwi (mm) | -7 [-226-+48] | | -6 [-187-+134] | | 4 [-138-+149] | | -16 [-265-+77] | |

Minimum and maximum values of the corresponding distributions in brackets
These figures correspond to the average losses/gains of the farms in the corresponding samples

## Table 2.12 Capitalisation of climate change 2012 (farms with 100% rented land)

| | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
|---|---|---|---|---|---|---|---|---|---|
| | | **NetRev/ha*** | **Rent/ha*** | **NetRev/ha*** | **Rent/ha*** | **NetRev/ha*** | **Rent/ha*** | **NetRev/ha*** | **Rent/ha*** |
| | | | | | **2012** | | | | |
| **CCSM4** | **Δ Net Rev/ha (%)** | **-54.25** | **3.21** | **-58.35** | **8.07** | **-63.88** | **4.60** | **-69.07** | **12.47** |
| | **Range [min-max]** | **[-92.6-252.9]** | **[-2.5-68.4]** | **[-107-404.6]** | **[1.7-94.1]** | **[-132.2-326.6]** | **[-9.9-80.9]** | **[-150.1-957.4]** | **[1.3-178.5]** |
| | Δ Net Rev/ha ($/ha) | -7,859 | 146 | -8,203 | 422 | -9,177 | 250 | -9,868 | 654 |
| | Range [min-max] | [-109092-34966] | [-57-1879] | [-134049-68410] | [5-4828] | [-133628-73749] | [-218-3317] | [-191644-132363] | [3-7362] |
| | Δ Net Rev ($*million) | -452 | 7 | -495 | 23 | -519 | 14 | -586 | 37 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.22 [0.99-1.54] | | 1.67 [1.45-2.17] | | 1.49 [1.28-1.96] | | 2.26 [1.87-2.90] | |
| | Δ Temp. auwi (ºC) | 1.22 [0.99-1.54] | | 1.67 [1.45-2.17] | | 1.49 [1.28-1.96] | | 2.26 [1.87-2.90] | |
| | Δ Rain. spsu (mm) | -4 [-84-+11] | | -14 [-104-+2] | | -6 [-92-+27] | | -21 [-170-+2] | |
| | Δ Rain. auwi (mm) | -2 [-109-+9] | | -10 [-135-+1] | | -4 [-119-+22] | | -15 [-221-+1] | |
| **MIROC5** | **Δ Net Rev/ha (%)** | **-74.39** | **4.41** | **-97.27** | **5.35** | **-42.80** | **13.90** | **-106.77** | **8.70** |
| | **Range [min-max]** | **[-122.8-155.9]** | **[-5.4-46.1]** | **[-189.2-316]** | **[-12.3-73.6]** | **[-122.6-116.1]** | **[-10.7-40.5]** | **[-244.1-241.2]** | **[-31.8-66.1]** |
| | Δ Net Rev/ha ($/ha) | -11,118 | 219 | -13,610 | 216 | -6,867 | 754 | -15,799 | 419 |
| | Range [min-max] | [-130595-94378] | [-324-2304] | [-155656-191238] | [-2156-3681] | [-102880-70244] | [-748-3807] | [-197196-145954] | [-2023-3305] |
| | Δ Net Rev ($*million) | -603 | 14 | -829 | 11 | -349 | 49 | -887 | 26 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.65 [1.28-2.13] | | 2.11 [1.58-2.58] | | 1.95 [1.33-2.50] | | 2.57 [1.93-3.09] | |
| | Δ Temp. auwi (ºC) | 1.65 [1.28-2.13] | | 2.11 [1.58-2.58] | | 1.95 [1.33-2.50] | | 2.57 [1.93-3.09] | |
| | Δ Rain. spsu (mm) | -4 [-119-+25] | | -9 [-171-+32] | | -23 [-102-+30] | | -13 [-142-+100] | |
| | Δ Rain. auwi (mm) | -3 [-71-+15] | | -4 [-102-+26] | | -18 [-61-+25] | | -9 [-84-+59] | |
| **MRI-CGCM3** | **Δ Net Rev/ha (%)** | **-38.59** | **3.71** | **-30.91** | **9.82** | **-41.88** | **6.41** | **4.43** | **21.83** |
| | **Range [min-max]** | **[-131.6-111.2]** | **[-20.1-35.3]** | **[-146.2-160.9]** | **[-16-43.2]** | **[-215.1-137.7]** | **[-37-39.4]** | **[-209.6-312.2]** | **[-19.5-70.9]** |
| | Δ Net Rev/ha ($/ha) | -5,443 | 156 | -5,070 | 567 | -7,006 | 383 | 241 | 1,347 |
| | Range [min-max] | [-105428-51797] | [-1507-3385] | [-101594-14379] | [-1167-4736] | [-123063-7581] | [-1934-2247] | [-162647-262457] | [-941-13096] |
| | Δ Net Rev ($*million) | -335 | 8 | -238 | 37 | -307 | 28 | 73 | 88 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Δ Temp. spsu (ºC) | 1.01 [0.85-1.48] | | 1.33 [1.00-1.69] | | 1.27 [0.83-1.69] | | 1.88 [1.26-2.56] | |
| | Δ Temp. auwi (ºC) | 1.01 [0.85-1.48] | | 1.33 [1.00-1.69] | | 1.27 [0.83-1.69] | | 1.88 [1.26-2.56] | |
| | Δ Rain. spsu (mm) | -7 [-103-+53] | | -18 [-127-+65] | | -8 [-116-+99] | | -38 [-176-+66] | |
| | Δ Rain. auwi (mm) | -3 [-61-+46] | | -14 [-75-+34] | | -7 [-69-+79] | | -30 [-104-+40] | |

Minimum and maximum values of the corresponding distributions in brackets
These figures correspond to the average losses/gains of the farms in the corresponding samples

## Table 2.13 Capitalisation of climate change 2014 (farms with 100% rented land)

| | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
|---|---|---|---|---|---|---|---|---|---|
| | | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* |
| | | | | | 2014 | | | | |
| CCSM4 | **Δ Net Rev/ha (%)** | **35.02** | **-1.31** | **46.98** | **-1.84** | **44.66** | **-2.62** | **63.89** | **-2.65** |
| | **Range [min-max]** | **[-5.9-54.0]** | **[-6.8-15.7]** | **[2.1-70.6]** | **[-9.7-19]** | **[8.3-63.6]** | **[-7.8-14.1]** | **[13.5-105.3]** | **[-15.2-24.5]** |
| | Δ Net Rev/ha ($/ha) | 7,389 | -75 | 9,890 | -105 | 9,626 | -128 | 13,435 | -153 |
| | Range [min-max] | [-89-72036] | [-1130-387] | [0-87945] | [-1665-829] | [0-87630] | [-1604-414] | [0-121747] | [-2458-1300] |
| | Δ Net Rev ($*million) | 475 | -8 | 647 | -11 | 579 | -10 | 865 | -16 |
| | | | | **Distribution of predicted changes of climate variables** | | | | | |
| | Δ Temp. spsu (ºC) | 1.31 [0.99-1.55] | | 1.75 [1.42-2.17] | | 1.58 [1.28-1.96] | | 2.36 [1.87-2.90] | |
| | Δ Temp. auwi (ºC) | 1.31 [0.99-1.55] | | 1.75 [1.42-2.17] | | 1.58 [1.28-1.96] | | 2.36 [1.87-2.90] | |
| | Δ Rain. spsu (mm) | -16 [-194-+13] | | -26 [-228-+9] | | -11 [-182-+21] | | -38 [-285-+2] | |
| | Δ Rain. auwi (mm) | -9 [-122-+9] | | -16 [-147-+8] | | -7 [-123-+17] | | -23 [-241-+2] | |
| MIROC5 | **Δ Net Rev/ha (%)** | **45.90** | **-2.85** | **54.12** | **-2.03** | **49.74** | **-2.20** | **68.87** | **-4.10** |
| | **Range [min-max]** | **[7.1-66.8]** | **[-11.1-14.5]** | **[-1.3-85]** | **[-15.4-25.5]** | **[11.8-74.9]** | **[-13-14.2]** | **[27.8-92.4]** | **[-20.2-20.5]** |
| | Δ Net Rev/ha ($/ha) | 9,378 | -142 | 10,586 | -120 | 9,911 | -122 | 13,837 | -207 |
| | Range [min-max] | [0-90710] | [-1469-1256] | [-1-105608] | [-1997-2247] | [0-101448] | [-1915-1079] | [0-130682] | [-2563-1663] |
| | Δ Net Rev ($*million) | 646 | -13 | 799 | -18 | 721 | -14 | 975 | -23 |
| | | | | **Distribution of predicted changes of climate variables** | | | | | |
| | Δ Temp. spsu (ºC) | 1.61 [1.25-2.16] | | 2.04 [1.55-2.69] | | 1.83 [1.26-2.60] | | 2.48 [1.84-3.16] | |
| | Δ Temp. auwi (ºC) | 1.61 [1.25-2.16] | | 2.04 [1.55-2.69] | | 1.83 [1.26-2.60] | | 2.48 [1.84-3.16] | |
| | Δ Rain. spsu (mm) | -11 [-233-+99] | | -30 [-357-+138] | | -27 [-230-+125] | | -26 [-308-+189] | |
| | Δ Rain. auwi (mm) | -7 [-152-+52] | | -16 [-233-+72] | | -18 [-150-+66] | | -15 [-201-+119] | |
| MRI-CGCM3 | **Δ Net Rev/ha (%)** | **28.26** | **-0.87** | **38.72** | **-2.63** | **39.71** | **-3.63** | **54.02** | **-3.14** |
| | **Range [min-max]** | **[5.2-77.2]** | **[-9.5-10.7]** | **[17.1-69.2]** | **[-14.3-7.6]** | **[15.9-68.1]** | **[-15.5-6.7]** | **[14.2-98.6]** | **[-14.8-14.6]** |
| | Δ Net Rev/ha ($/ha) | 5,798 | -32 | 8,275 | -99 | 8,597 | -134 | 11,522 | -118 |
| | Range [min-max] | [0-58044] | [-710-1943] | [0-88842] | [-2019-1551] | [0-95763] | [-3097-838] | [0-114317] | [-2340-1102] |
| | Δ Net Rev ($*million) | 371 | -5 | 493 | -7 | 483 | -8 | 666 | -9 |
| | | | | **Distribution of predicted changes of climate variables** | | | | | |
| | Δ Temp. spsu (ºC) | 1.07 [ 0.81-2.00] | | 1.32 [0.99-1.87] | | 1.25 [0.83-1.73] | | 1.92 [1.11-3.02] | |
| | Δ Temp. auwi (ºC) | 1.07 [ 0.81-2.00] | | 1.32 [0.99-1.87] | | 1.25 [0.83-1.73] | | 1.92 [1.11-3.02] | |
| | Δ Rain. spsu (mm) | -14 [-195-+77] | | -6 [-148-+186] | | 11 [-107-+200] | | -23 [-193-+123] | |
| | Δ Rain. auwi (mm) | -8 [-190-+46] | | -6 [-140-+129] | | 5 [-130-+149] | | -17 [-152-+75] | |

Minimum and maximum values of the corresponding distributions in brackets
These figures correspond to the average losses/gains of the farms in the corresponding samples

Using expressions (2.13) and (2.14) in the methodological section, we also compute likely changes in net revenues and rental prices in monetary terms. Table 2.10-2.13 show the average losses or gains per hectare (or the implicit value of climate change per hectare). Furthermore, we compute the total losses or gains for farms in the corresponding samples and under the corresponding scenarios. For instance, a warmer and drier future for those farms in the 2012 sample would reduce total net revenues by approximately -$176-(-) $704 million Mexican pesos (losses/gains of -$887-(+) $73 in farms with 100% rented land). In contrast, the total gain, capitalised in land rental prices, would be between +$43 and +$233 million Mexican pesos (between +$7 and +$88 in farms with 100% rented land). For farms in the 2014 sample, the net revenues model predicts total gains between +$1,697 and $5,014 million Mexican pesos (between $371 and $975 in farms with 100% rented land). In contrast, the rental price model predicts losses and gains between -$45 and +$17 million Mexican pesos (between -$23 and -$5 in farms with 100% rented land).

Overall, the net revenues and rental prices models predict different effects of climate change on agriculture. When the direction (sign) of the total effect coincides, the net revenues equation tends to predict larger effects of climate change on agriculture than the rental price model. There are many reasons that can explain such finding. For example, we find empirical evidence that observed net revenues at the end of the agricultural year are not equal to rental prices agreed at the beginning of the agricultural year, which in theory should be equivalent. These deviations arise because the NAS does not collect enough information to precisely computing net revenues as in Palmquist (1989) and therefore, the variable suffers from measurement errors. Furthermore, net revenues are subject to unexpected events, e.g. weather shocks, plagues, or water shortages, that might also cause the huge variation in Figures 2.7a-2.7h. If such variation is not accounted for in the Ricardian hedonic models, especially in developing countries where reliable data on land prices is not available, the assessments of the capitalisation of climate change in land rents may lead to biased predictions. Thus, in this chapter, we find that predictions drawn from net revenues tend to overstate the effect of climate change on land rents.

## 2.5. Conclusions

Taking advantage of two waves of cross-sectional data on net revenues and land rental prices of the same farmsteads, this chapter examines the appropriateness of using annual net revenues in Ricardian hedonic models. Unlike previous studies in Mexico, this chapter uses farm-level data, which is a representative sample of the Mexican agriculture sector, to estimate a Ricardian hedonic model. Using net revenues from 58,743 farms in the 2014 sample, which is a representative sample of the whole agriculture sector in Mexico, we encounter a positive economic impact of climate change on Mexican agriculture. Table 2.25 in Appendix A2.5 uses the set of parameter estimates in Table 2.4 and shows that current net revenues would likely increase between 22.64% and 55.60% by 2060 under different climate change scenarios. This finding contradicts previous assessments in Mexico. Using self-reported land values, Mendelsohn et al. (2010) predict average losses between 42% and 54%. Such an assessment uses data on 621 rural households, which is not by any means a representative sample of the entire sector. Furthermore, farmers in rural areas might not have the expertise to value their land correctly since land transactions in rural areas do not take place very often. Therefore, we believe that the two-abovementioned issues lead to different conclusions in Mendelsohn et al. (2010).

Galindo et al. (2015) use a municipality-level panel data on net revenues and predict average losses between 19% and 36% of the current net revenues. These authors do not control for soil characteristics in the Ricardian Hedonic model and data aggregation at the municipality level hides heterogeneity among farms within the same municipality. According to Timmins (2006), unobservable farms' heterogeneity, such as land uses (crop choices), is part of the error term and may depend on climate variables in the Ricardian model. Thus, Galindo et al's assessments may suffer from endogeneity issues and might be inaccurate. Furthermore, Galindo et al assume additively separable effects of temperature and rainfall, and consequently, do not include the interaction term in the main regression. Under such circumstances, we argue that our results outperform previous Ricardian studies in Mexico.

The quality of this data also permits the estimation of Ricardian hedonic models using net revenues and land rental prices from the same farmsteads. By comparing parameter estimates, implicit prices of land attributes and assessments of the effects of climate change on land rents resulting from such models, we show that using net revenues or land rental prices lead to different conclusions.

Both the net revenues and rental price models corroborate that land rents are sensitive to climate, which is in line with previous investigations. There is a non-linear relationship between temperature/rainfall and land rents. The significance of the interaction term between seasonal temperature and rainfall confirms the argument of Fezzi and Bateman (2015) that the effect of global warming also depends on the current level of rainfall. Aside from the effect of climate on land rents, we also encounter that there exists a non-linear relationship between land rents and total area. The association between access to markets,[91] or to water sources,[92] and land rents is ambiguous. Moreover, the availability of an irrigation system and an electricity grid are desirable land attributes that increase land rents and farms that use ejidal lands tend to obtain lower net revenues but higher rental prices.

We find strong empirical evidence that the use of net revenues (observed at the end of the agricultural year) or land rental prices (agreed at the beginning of the agricultural year) in a

[91] Distance from the farm to urban areas and road density
[92] Perennial water bodies and rivers

Ricardian hedonic model leads to different results. Using data on the same farmsteads, we find that rental prices, defined in Palmquist (1989), are not equal to net revenues as previous studies assumed (Mendelsohn et al., 1994). Unexpected events and measurement errors are likely to cause a huge variation in net revenues, while rental prices seem to be more stable indicators of land rents. In this regard, we find that the same set of explanatory variables explain 9%-23% and 40%-51% of the variation of net revenues and rental prices in the corresponding farms respectively. If such variation is not accounted for in the Ricardian hedonic model, then, parameter estimates would lead to misleading assessments of the effect of climate change on agriculture.

To investigate how the variation in net revenues influences assessments of the effect of climate change on agriculture, we combine parameter estimates from the net revenues and rental price models using data on the same farmsteads with the climate projections of three GCMs. The main findings indicate that, for the 2012 sample, in the event of a warmer and drier future the net revenues model predicts average losses between -3.09% and -14.78% of the current net revenue per hectare. In contrast, the rental price model predicts average benefits between +4.03% and +13.12% of the current rental price per hectare. Regarding farms in the 2014 sample, the net revenues model predicts large benefits, which vary between +24.22% and +67.46% while the rental price model predicts losses/benefits between -1.85% and +1.43% of the current rental price per hectare. Thus, using net revenues or rental prices as indicators of Ricardian rents leads to different predictions about the effects of climate change on agriculture. When the direction of such effects coincides, the net revenues equation predicts larger effects than the rental price equation. Under these circumstances, policy-makers and future research should take into account the variation of annual net revenues, which mainly arise from unexpected events and measurement errors, to assess the effect of climate change on land rents. Future empirical studies should use net revenues in contexts where land values are not observable. Sometimes researchers observe land values; however, such measures may not reflect the Ricardian rent due to government regulations or self-reporting issues. Under such circumstances, one would prefer net revenues to be the dependent variable in Ricardian studies if the following conditions hold:

1. there is high-quality data on annual costs, especially on the cost of different types of capital e.g. machinery, equipment (purchasing price, scrap value and lifespan), facilities, biological capital (cost of oxen) and debt (interests);
2. if agriculture is highly subsidised, subsidies must be deducted from net revenues or accounted for in the Ricardian hedonic regression. To do so, future studies must have detailed information on the subsidies. This is important because such transfers prevent the least productive farmers, which without the subsidy obtain negative net revenues, to exit the market (this breaks the economic principle of that Ricardian rents are non-negative);
3. when agriculture is highly subsidised, subsidies could artificially increase the value of land since the owner would expect a higher stream of income (current income plus the subsidy) by keeping his land in agriculture. Since there is so much uncertainty in the continuity of the subsidisation programme, e.g. a new government may eliminate agricultural subsidies, it would be difficult to account for the future stream of subsidies in the analysis of land values. Thus, by using annual net revenues, future studies can control for the existence of subsidies more precisely.
4. the government does not intervene in the land market either by regulating land or rental prices;
5. the government does not implement regulations on output or input prices; and,

6. a panel dataset is available, which minimise the risk of measuring land rents incorrectly, e.g. future studies would minimise the effect of an unusual bad year (with negative net revenues) on the parameter estimates by using a panel of farms.

To interpret the findings in this chapter the reader should be aware of some weaknesses. First, there might be some omitted variables in the Ricardian Hedonic models that can be correlated with climate, e.g. crop and livestock choices. In this regard, potential endogeneity issues may cause some biases in the parameter estimates, especially for estimates on net revenue models. Second, as discussed earlier on in the chapter, the net revenues variable does not always include the cost of buildings and the cost of biological capital since the NAS does not collect sufficient information to compute such costs. Therefore, net revenues from some farms, such as dairy or beef cattle farms, may be larger than their actual values because we do not subtract the annual cost of buildings of biological capital from the total revenue. Third, the Ricardian approach is not able to deal with carbon fertilisation effects since there is no enough variation on Carbon Dioxide (CO2) concentrations across the Mexican territory. Fourth, predictions about the effect of climate change on net revenues and rental prices assume that factors other than climate remained unchanged in the corresponding scenarios. Among other things, technological progress, new varieties, and population growth (higher demand for agricultural land) will influence the future of the agriculture sector. Further steps of this research should combine data from multiple years to identify the capitalisation of climate change on land rents. Moreover, future research should also allocate more effort to rectify accounting problems in the computation of net revenues.

## References


Abidoye, B.O., Kurukulasuriya, P., Reed, B. and Mendelsohn, R., 2017. Structural ricardian analysis of South-East Asian agriculture. *Climate Change Economics*, *8*(03), p.1740005.

Adams, R., Glyer, J.D. and McCarl, B., 1989. The economic effects of climate change on US agriculture: a preliminary assessment. *The Potential Effects of Global Climate Change on the United States*, *1*, pp.4-1.

Adams, R.M. and McCarl, B., 2001. Agriculture: agronomic-economic analysis. *Global Warming and the American Economy: A Regional Assessment of Climate Change, Edward Elgar, Northhampton, MA*, pp.18-31.

Adams, R.M., Rosenzweig, C., Peart, R.M., Ritchie, J.T., McCarl, B.A., Glyer, J.D., Curry, R.B., Jones, J.W., Boote, K.J. and Allen Jr, L.H., 1990. Global climate change and US agriculture. *Nature*, *345*(6272), p.219.

Anselin, L., 2010. Thirty years of spatial econometrics. *Papers in regional science*, *89*(1), pp.3-25.

Ater, P.I. and Aye, G.C., 2012. Economic impact of climate change on Nigerian maize sector: A ricardian analysis. *Wessex Institute of Technology (WIT) Transactions on Ecology and the Environment*, *162*, pp.231-239.

Batsuuri, T. and Wang, J., 2017. The impacts of climate change on Nomadic livestock husbandry in Mongolia. *Climate Change Economics*, *8*(03), p.1740003.

Bezabih, M., Di Falco, S. and Mekonnen, A., 2014. *On the impact of weather variability and climate change on agriculture: evidence from Ethiopia* (No. dp-14-15-efd).

Bosello, F. and Zhang, J., 2005. Assessing climate change impacts: agriculture.

Brassel, K.E. and Reif, D., 1979. A procedure to generate Thiessen polygons. *Geographical Analysis*, *11*(3), pp.289-303.

Burniaux, J.M. and Lee, H.L., 2003, June. Modelling land use changes in GTAP. In *Proceedings of the 6th Annual Conference on Global Economic Analysis, The Hague, The Netherlands* (Vol. 1214).

Cameron, A.C. and Trivedi, P.K., 2011. *Microeconometrics using stata: revised edition* (Vol. 2). College Station, TX: Stata press.

Confalonieri, R., Gusberti, D., Bocchi, S. and Acutis, M., 2006. The CropSyst model to simulate the N balance of rice for alternative management. *Agronomy for sustainable development*, *26*(4), pp.241-249.

Crosson, P., 1993. Impacts of climate change on the agriculture and economy of the Missouri, Iowa, Nebraska, and Kansas (MINK) region. *Agricultural Dimensions of Global Climate Change, St. Lucie Press, Delray Beach, FL*, pp.117-135.

Darwin, R., 1999. The impact of global warming on agriculture: A Ricardian analysis: Comment. *American Economic Review*, *89*(4), pp.1049-1052.

Deressa, T.T. and Hassan, R.M., 2009. Economic impact of climate change on crop production in Ethiopia: evidence from cross-section measures. *Journal of African economies*, *18*(4), pp.529-554.

Deressa, T.T., 2007. *Measuring the economic impact of climate change on Ethiopian agriculture: Ricardian approach*. The World Bank.

Deschênes, O. and Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, *97*(1), pp.354-385.

Deschênes, O. and Greenstone, M., 2012. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: reply. *American Economic Review*, *102*(7), pp.3761-73.

Di Falco, S., Yesuf, M., Kohlin, G. and Ringler, C., 2012. Estimating the impact of climate change on agriculture in low-income countries: Household level evidence from the Nile Basin, Ethiopia. *Environmental and Resource Economics*, *52*(4), pp.457-478.

Dinar, A., Mendelsohn, R., Evenson, R., Parikh, J., Sanghi, A., Kumar, K., McKinsey, J. and Lonergan, S., 1998. *Measuring the impact of climate change on Indian agriculture*. The World Bank.

Edwards, W. M., 2011. Estimating farm machinery costs. Iowa State University, Department of Economics.

Eid, H.M., El-Marsafawy, S.M. and Ouda, S.A., 2007. Assessing the economic impacts of climate change on agriculture in Egypt: a Ricardian approach.

FAO-UNESCO, 1974. Soil map of the world. Technical report, FAO-UNESCO.

FAO-UNESCO, 1997. Soil map of the world. Technical report, FAO-UNESCO.

Fezzi, C. and Bateman, I., 2015. The impact of climate change on agriculture: Nonlinear effects and aggregation bias in Ricardian models of farmland values. *Journal of the Association of Environmental and Resource Economists*, *2*(1), pp.57-92.

Fisher, A.C., Hanemann, W.M., Roberts, M.J. and Schlenker, W., 2012. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. *American Economic Review*, *102*(7), pp.3749-60.

Fleischer, A., Lichtman, I., and Mendelsohn, R., 2008. Climate change, irrigation, and Israeli agriculture: Will warming be harmful? *Ecological economics*, 65(3), pp. 508-515.

Freeman III, A.M., 1974. On estimating air pollution control benefits from land value studies. *Journal of Environmental Economics and Management*, *1*(1), pp.74-83.

Galindo, L.M. and Reyes, O., 2015. Climate change, irrigation and agricultural activities in Mexico: A Ricardian analysis with panel data. *Journal of Development and Agricultural Economics*, *7*(7), pp.262-273.

García, M. and Viladrich, M., 2009. The economic relevance of climate variables in agriculture: The case of Spain. *Economía agraria y recursos naturales*, *9*(2), pp.149-180.

Gebreegziabher, Z., Mekonnen, A., Deribe, R., Abera, S. and Kassahun, M.M., 2013. *Crop-Livestock inter-linkages and climate change implications for Ethiopia's agriculture: A Ricardian approach* (No. dp-13-14-efd).

Golub, A., Hertel, T.W. and Sohngen, B., 2009. 10 Land use modelling in a recursively dynamic GTAP framework. *Economic analysis of land use in global climate change policy*, *14*, p.235.

Hartkamp, A.D., De Beurs, K., Stein, A. and White, J.W., 1999. Interpolation techniques for climate variables.

Heath, J.R., 1992. Evaluating the impact of Mexico's land reform on agricultural productivity. *World development*, *20*(5), pp.695-711.

Hertel, T.W., 2011. The global supply and demand for agricultural land in 2050: A perfect storm in the making?. *American Journal of Agricultural Economics*, *93*(2), pp.259-275.

Hidalgo, H.G. and Alfaro, E.J., 2015. Skill of CMIP5 climate models in reproducing 20th century basic climate features in Central America. *International Journal of Climatology*, *35*(12), pp.3397-3421.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. and Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology*, *25*(15), pp.1965-1978.

Howitt, R.E., Lund, J.R., Kirby, K.W., Jenkins, M.W., Draper, A.J., Grimes, P.M., Ward, K.B., Davis, M.D., Newlin, B.D., Van Lienden, B.J. and Cordua, J.L., 1999. Integrated economic-engineering analysis of California's future water supply. *Project Completion Rep*.

INEGI, 2014a. Conjunto de datos vectoriales Perfiles de suelos. Escala 1:1 000 000. Retrieved from: http://www.beta.inegi.org.mx/app/biblioteca/ficha.html?upc=702825267636

INEGI, 2014b. Guía para la interpretación de cartografía edafológica. INEGI, Mexico.

IPCC, 2013. Summary for policymakers. Book section, Cambridge, United Kingdom and New York, NY, USA.

Jain, S., 2007. *An empirical economic assessment of impacts of climate change on agriculture in Zambia*. The World Bank.

John, J.A. and Draper, N.R., 1980. An alternative family of transformations. *Applied Statistics*, pp.190-197.

Johnson, N.L., 2001. Tierra y libertad: will tenure reform improve productivity in Mexico's ejido agriculture?. *Economic Development and Cultural Change*, *49*(2), pp.291-309.

Kabubo-Mariara, J. and Karanja, F.K., 2007. *The economic impact of climate change on Kenyan crop agriculture: A Ricardian approach*. The World Bank.

Kabubo-Mariara, J., 2009. Global warming and livestock husbandry in Kenya: Impacts and adaptations. *Ecological Economics*, *68*(7), pp.1915-1924.

Katz, R.W., 1979. Sensitivity analysis of statistical crop—weather models. *Agricultural Meteorology*, *20*(4), pp.291-300.

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N., Meinke, H., Hochman, Z. and McLean, G., 2003. An overview of APSIM, a model designed for farming systems simulation. *European journal of agronomy*, *18*(3-4), pp.267-288.

Kurukulasuriya, P. and Mendelsohn, R., 2007. Endogenous irrigation: The impact of climate change on farmers in Africa. *The World Bank.*

Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H.M., Fosu, K.Y., Gbetibouo, G., Jain, S. and Mahamadou, A., 2006. Will African agriculture survive climate change?. *The World Bank Economic Review*, *20*(3), pp.367-388.

Lang, G., 2007. Where are Germany's gains from Kyoto? Estimating the effects of global warming on agriculture. *Climatic Change*, *84*(3-4), pp.423-439.

Lee, H.L., 2005. Incorporating agro-ecologically zoned land use data and landbased greenhouse gases emissions into the GTAP framework. In *8th annual conference on Global Economic Analysis, Lübeck, Germany*.

Lee, H.L., Hertel, T.W. and Rose, S., 2009. An integrated global land use database for CGE analysis of climate policy options. In *Economic analysis of land use in global climate change policy* (pp. 92-108). Routledge.

Lippert, C., Krimly, T. and Aurbacher, J., 2009. A Ricardian analysis of the impact of climate change on agriculture in Germany. *Climatic change*, *97*(3-4), p.593.

Liverman, D.M., Terjung, W.H., Hayes, J.T. and Mearns, L.O., 1986. Climatic change and grain corn yields in the North American Great Plains. *Climatic Change*, *9*(3), pp.327-347.

Maddison, D., 2000. A hedonic analysis of agricultural land prices in England and Wales. *European Review of Agricultural Economics*, *27*(4), pp.519-532.

Maddison, D., 2009. A Spatio-temporal Model of Farmland Values. Journal of Agricultural Economics, 60(1), pp.171-189.

Maddison, D., Manley, M., Kurukulasuriya, P., 2007. The Impact of Climate Change on African Agriculture: A Ricardian Approach. Policy Research Working Paper; No. 4306. *World Bank*, Washington, DC. © World Bank.

Mano, R. and Nhemachena, C., 2007. *Assessment of the economic impacts of climate change on agriculture in Zimbabwe: A Ricardian approach*. The World Bank.

Massetti, E. and Mendelsohn, R., 2011. Estimating Ricardian models with panel data. *Climate Change Economics*, *2*(04), pp.301-319.

Massetti, E., Mendelsohn, R., and Chonabayashi, S., 2015. Using degree days to value farmland. *FEEM Working Paper* No. 012.2015.

McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D.P. and Freebairn, D.M., 1996. APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. *Agricultural systems*, *50*(3), pp.255-271.

Mendelsohn, R. and Dinar, A., 2003. Climate, water, and agriculture. *Land economics*, *79*(3), pp.328-341.

Mendelsohn, R. and Nordhaus, W.D., 1992. *The Impact of Climate on Agriculture: A Ricardian Approach* (No. 1010). Cowles Foundation for Research in Economics, Yale University.

Mendelsohn, R. and Nordhaus, W.D., 1999. The impact of global warming on agriculture: A Ricardian analysis: Reply. *American Economic Review*, *89*(4), pp.1046-1048.

Mendelsohn, R., 2014. The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture*, *13*(4), pp.660-665.

Mendelsohn, R., Arellano-Gonzalez, J. and Christensen, P., 2010. A Ricardian analysis of Mexican farms. *Environment and Development Economics*, *15*(2), pp.153-171.

Mendelsohn, R., Dinar, A. and Sanghi, A., 2001. The effect of development on the climate sensitivity of agriculture. *Environment and Development Economics*, *6*(1), pp.85-101.

Mendelsohn, R., Nordhaus, W.D. and Shaw, D., 1994. The impact of global warming on agriculture: a Ricardian analysis. *The American economic review*, pp.753-771.

Mendelsohn, R.O. and Dinar, A., 2009. *Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects*. Edward Elgar Publishing.

Molua, E.L. and Lambi, C.M., 2007. *The Economic Impact Of Climate Change On Agriculture In Cameroon, Volume 1of 1*. The World Bank.

Nelson, G.C., Van Der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H. and von Lampe, M., 2014. Agriculture and climate change in global scenarios: why don't the models agree. *Agricultural Economics*, *45*(1), pp.85-101.

Palatnik, R.R. and Roson, R., 2009. Climate change assessment and agriculture in general equilibrium models: Alternative modeling strategies.

Palmquist, R.B. and Danielson, L.E., 1989. A hedonic study of the effects of erosion control and drainage on farmland values. *American journal of agricultural economics*, *71*(1), pp.55-62.

Palmquist, R.B., 1989. Land as a differentiated factor of production: A hedonic model and its implications for welfare measurement. *Land economics*, *65*(1), pp.23-28.

Patton, M. and McErlean, S., 2003. Spatial effects within the agricultural land market in Northern Ireland. *Journal of Agricultural Economics*, *54*(1), pp.35-54.

Reinsborough, M.J., 2003. A Ricardian model of climate change in Canada. *Canadian Journal of Economics/Revue canadienne d'économique*, *36*(1), pp.21-40.

Ricardo, D., 1817. *Principles of political economy and taxation*. G. Bell.

Ritchie, J.T., Godwin, D.C. and Otter-Nacke, S., 1985. CERES-Wheat. A simulation model of wheat growth and development. *ARS (1985).(págs. 159-175). US Department of Agriculture*.

Ronneberger, K., Berrittella, M., Bosello, F. and Tol, R.S., 2009. KLUM@ GTAP: Introducing biophysical aspects of land-use decisions into a computable general equilibrium model a coupling experiment. *Environmental modeling & assessment*, *14*(2), pp.149-168.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, *82*(1), pp.34-55.

Rosenzweig, C. and Parry, M.L., 1994. Potential impact of climate change on world food supply. *Nature*, *367*(6459), pp.133-138.

Rosenzweig, C., 1985. Potential CO 2-induced climate effects on North American wheat-producing regions. *Climatic Change*, *7*(4), pp.367-389.

Runge, C.F., 2010. Climate Change and Agriculture: An Economic Analysis of Global Impacts, Adaptation and Distributional Effects. New Horizons in Environmental Economics.

Seo, N. and Mendelsohn, R., 2007. *A Ricardian analysis of the impact of climate change on Latin American farms*. The World Bank.

Seo, S. N., Mendelsohn, R., Dinar, A., Hassan, R., and Kurukulasuriya, P., 2009. A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa. *Environmental and Resource Economics*, 43(3), pp. 313-332.

Seo, S.N. and Mendelsohn, R., 2008a. *A structural Ricardian analysis of climate change impacts and adaptations in African agriculture*. The World Bank.

Seo, S.N. and Mendelsohn, R., 2008b. Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management 1. *Agricultural economics*, *38*(2), pp.151-165.

Seo, S.N. and Mendelsohn, R., 2008c. CLIMATE CHANGE IMPACTS ON LATIN AMERICAN FARMLAND VALUES: THE ROLE OF FARM TYPE. *Revista de Economia e Agronegocio*, *6*(2).

Seo, S.N.N., Mendelsohn, R. and Munasinghe, M., 2005. Climate change and agriculture in Sri Lanka: a Ricardian valuation. *Environment and development Economics*, *10*(5), pp.581-596.

Singh, A.K., Tripathy, R. and Chopra, U.K., 2008. Evaluation of CERES-Wheat and CropSyst models for water–nitrogen interactions in wheat crop. *Agricultural water management*, *95*(7), pp.776-786.

Tabios III, G.Q. and Salas, J.D., 1985. A COMPARATIVE ANALYSIS OF TECHNIQUES FOR SPATIAL INTERPOLATION OF PRECIPITATION 1. *JAWRA Journal of the American Water Resources Association*, *21*(3), pp.365-380.

Thiessen, A.H., 1911. Precipitation averages for large areas. *Monthly weather review*, *39*(7), pp.1082-1089.

Thompson, L.M., 1969. Weather and technology in the production of wheat in the United States. *Journal of Soil and Water Conservation*.

Timmins, C., 2006. Endogenous land use and the Ricardian valuation of climate change. *Environmental and Resource Economics*, *33*(1), pp.119-142.

Van Passel, S., Massetti, E. and Mendelsohn, R., 2017. A Ricardian analysis of the impact of climate change on European agriculture. *Environmental and Resource Economics*, *67*(4), pp.725-760.

Wang, J., Huang, J., Zhang, L. and Li, Y., 2014. Impacts of climate change on net crop revenue in North and South China. *China Agricultural Economic Review*, *6*(3), pp.358-378.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S. and Zhang, L., 2008. *Can China continue feeding itself? The impact of climate change on agriculture*. The World Bank.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S. and Zhang, L., 2009. The impact of climate change on China's agriculture. *Agricultural Economics*, *40*(3), pp.323-337.

White, J.W., Hoogenboom, G., Kimball, B.A. and Wall, G.W., 2011. Methodologies for simulating impacts of climate change on crop production. *Field Crops Research*, *124*(3), pp.357-368.

Whittaker, J., Whitehead, C. and Somers, M., 2005. The neglog transformation and quantile regression for the analysis of a large credit scoring database. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *54*(5), pp.863-878.

Williams, J.R., 1990. The erosion-productivity impact calculator (EPIC) model: a case history. *Phil. Trans. R. Soc. Lond. B*, *329*(1255), pp.421-428.

Williams, J.R., Jones, C.A. and Dyke, P.T., 1984. A modeling approach to determining the relationship between erosion and soil productivity. *Transactions of the ASAE*, *27*(1), pp.129-0144.

Wineman, A. and Crawford, E.W., 2017. Climate change and crop choice in Zambia: A mathematical programming approach. *NJAS-Wageningen Journal of Life Sciences*, *81*, pp.19-31.

Xin, X., Lin, T., Liu, X., Wan, G. and Zhang, Y., 2013. The impacts of climate change on the People's Republic of China's grain output: regional and crop perspective. *China Agricultural Economic Review*, *5*(4), pp.434-458.

Yang, H.S., Dobermann, A., Lindquist, J.L., Walters, D.T., Arkebauer, T.J. and Cassman, K.G., 2004. Hybrid-maize—a maize simulation model that combines two crop modeling approaches. *Field Crops Research*, *87*(2-3), pp.131-154.

Zhai, F., Lin, T. and Byambadorj, E., 2009. A General Equilibrium Analysis of the Impact of Climate Change on Agriculture in the People’s Republic of China. Asian Development Review, Vol. 26 (1), pp. 206-225.

# Appendix

## *A2.1. Agronomic models*

Since 1970, several researchers apply agronomic models (or crop simulations) in different places around the world. For example, Thompson (1969) use these models to predict crop yields under different climatic conditions by using historical records in the United States. Katz (1979) develops a sensitivity analysis of crop-weather models. Furthermore, Rosenzweig (1985) and Liverman et al. (1986) apply this framework to analyse wheat and maize yields in North America, respectively.

The application of agronomic models involves field or laboratory experiments in which researchers manipulate climate conditions and carbon dioxide concentrations to simulate the growing phase. Additionally, agronomists may also modify soil and the characteristics of the plants to examine yield responses (Adams et al., 1989). Thus, the results of such experiments can be extrapolated to obtain an aggregate measure of the effect of climate change on agriculture (Rosenzweig and Parry 1994) or could be introduced into a more general economic model such as partial equilibrium models to identify the effects of climate changes on agriculture (Adams et al., 1989, 1990; Crosson, 1993). The second option is widely known as the 'agro-economic' model in the existing literature since both agronomic and economic variables enter into the model (Adams and McCarl, 2001).

According to White et al. (2011), who conduct a literature review on agronomic models and consider 221 peer-reviewed papers, previous studies analyse the effects of climate change on the United States and Europe, 55 and 64 papers respectively. These authors also encounter that simulations of wheat, maize, rice and soybean yields are popular within this strand of literature. White et al. (2011) also highlight that most of the research articles assess the impact of climate change on crop yields using the Crop Environment Resource Synthesis model (CERES-63 papers), [93] the Erosion Productivity Impact Calculator (EPIC-25 papers), [94] Agricultural Production Systems sIMulator (APSIM-13 papers)[95] and Cropping Systems Simulation Model (CropSyst-9 papers).[96]

Nowadays, agronomic models are available for almost all important crops and these are able to predict biomass or grain yields. To provide an example of the agronomic model, we describe the CERES-Maize model. It predicts the maize yields, which depend on solar radiation, temperature, phenology, and plant canopy. Yang et al. (2004) define light interception, photosynthesis, crop dry matter, CO2 assimilation rate, the total leaf biomass and leaf areas/sizes as follows:

$$PAR = 0.5IR(1 - e^{-kLAI}) \tag{18}$$

where $PAR$ is the photosinthetically active radiation, $IR$ is the total incident solar radiation, $k$ is the light extinction coefficient and $LAI$ stands for the leaf area index;

$$DM = PAR * RUE \tag{19}$$

where $DM$ is the total amount of crop dry matter and $RUE$ indicates the radiation use efficiency;

[93] The CERES model is able to simulate crop growth, its development process and yield once weather, genetics, soil, planting, irrigation and nitrogen fertilization features have been incorporated into the analysis. Some authors have applied this technique to estimate the effects of climate on crop production, especially on wheat (Ritchie et al., 1985; Singh et al., 2008). One of the most important characteristic of this technique is that it incorporates a large number of crop parameters, which allows us for deeper analyses, but at the same time, it is more complex and requires more effort to calibrate it.

[94] The EPIC model examines the effect of soil erosion on soil productivity (Williams et al., 1984). Thus, it simulates erosion, plant growth and several related process including economic assessments for the cost of erosion. Williams (1990) states that the components of this model can be packaged into nine divisions: hydrology, weather, erosion, nutrients, soil temperature, plant growth, tillage, plant environment and economics. All this set of factors is included into its simulations process.

[95] The Agricultural Production Systems Research Unit in Australia designs the APSIM model to simulate biophysical process in farming systems. This model simulates the interaction between economic and ecological factors and its outcomes depend on climate change or risk simulations. Overall, the model analyses different crops, pastures and trees, soil features, water availability, some transformations, erosion and a vast set of management issues. Moreover, this method has been applied for analyzing farmers' decisions, production design, assess the impact of a changing climate and other applications (McCown et al. 1996).

[96] The CropSyst model simulates growth and development of all herbaceous crops (Confalonieri et al., 2006). It uses historical records, different crops, daily simulation and is linked to Geographic Information System (GIS) software. In contrast with the CERES model, these simulations have been simplified in order to make their calibration easier (less number of crop parameters are considered). Thus, CropSyst models offer the possibility of large-scale simulations (Singh et al., 2008)

$$AS = \int_{L=0}^{LAI} AS_m \left(1 - e^{-EPAR_{L/AS_m}}\right) dL \tag{20}$$

where $AS$ is the gross CO2 assimilation rate, $L$ the depth of plant canopy, $L = 0$ at the top of the plant and $L = LAI$ at the bottom, $AS_m$ represents the maximum level of $AS$ and $E$ is the initial light use efficiency;

$$LW = \left({}^{PLA}/_{267}\right)^{1.25} \tag{21}$$

where $LW$ is the total leaf biomass and $PLA$ is the total plant leaf area;

$$SLA = {}^{LW}/_{PLA} \tag{22}$$

where $SLA$ is the daily specific leaf area;

$$SF = 0.7\left({}^{sumDTT}/_{P5}\right)^{4} \tag{23}$$

where $SF$ denotes the senescent leaf area, $sumDTT$ is the cumulative growing degree days from the start of silking, $P5$ is the growing degree days from silking to maturity;

$$sumDTT = \frac{sumDTT + DTT}{1 - LSR} \tag{24}$$

$DTT$ indicates daily effective temperature and $LSR$ is the stress rate from low temperatures and light competition. By solving this set of equations, the CERES-Maize model predicts the leaf area index, dry matter accumulation and biomass, which are sensitive to changes in climate and other factors.

Another example of the agronomic models is the CROPGRO-Soybean model, which indicates that soybean biomass and grain yield responses depend on management practices, environmental conditions, genetic yield potential and causes of spatial yield variability. The simplest version of this model is as follows:

$$Y_{soy} = h(m, f, g, G) \tag{25}$$

where $Y_{soy}$ stands for soybean yields or biomass, $m$ is a vector of management conditions, $g$ a vector of genetics' characteristics [97] and $G$ account for spatial factors (location). The CROPGRO-Soybean model comprises data on the compositions of tissues, partitions of traits, sensitivity to temperature,[98] light, plant water deficit, life cycles, vegetative traits, leaf traits, potential seed fill duration, seed size and seed composition.

Overall, the agronomic models identify the relationship between climate variables, e.g. temperature, rainfall or both, on yields (biomass). Also included in the analysis are management practices, genetics and the effect of carbon fertilisation. Despite alternative approaches in the literature cannot accommodate carbon fertilisation such as the Ricardian method, agronomic models consider carbon fertilisation in their simulations about the effects of climate change on agriculture via yields. On the other hand, this approach cannot account for adaptation strategies, its calibration requires a vast set of information and the model is sensitive to selection of parameters for its calibration. Given these disadvantages, especially its inability to account for farmers' adaptation, prevent us to use agronomic models in this research.

### *A2.2. Computable general equilibrium models*

Computable general equilibrium models represent an alternative tool for estimating the interaction among economic sectors. Within this framework, the corresponding agents optimise an objective function by finding the optimal resources allocation subject to a set of constraints (Wineman and Crawford, 2017). Depending on the level of aggregation, researchers can use computable general equilibrium models to examine how farmers react to particular policies or external climatic shocks within a complex system. For example, Howitt et al. (1999) examine

[97] Genetic variables include slope of the relative response of development to photoperiod with time, time between emergence and first flower, maximum leaf photosynthesis rate at 30ºC, 350 vpm $CO_2$, high light and other features.
[98] It uses a sinus curve to identify the relationship between temperature and yields.

water management and agricultural production in California, US. Likewise, Zhai et al. (2009) use a computable general equilibrium model to assess the effects of climate on agriculture in China. Palatnik and Roson (2009) present an overview of applications of computable general equilibrium models around the world examining agro-environmental issues, including the impact of climate change on agriculture as other authors do (Burniaux and Lee, 2003; Lee, 2005; Bosello and Zhang, 2005; Ronneberger et al., 2009; Lee et al., 2009; Golub et al., 2009).

One of the main advantages of the application of computable general equilibrium models is that such models accommodate adaptation processes within a complex system. This framework analyses the entire economy thereby, it is able to simulate direct and indirect effects (via other sectors) of external shocks on agriculture. Within this context, climate change represents an exogenous shock that originates endogenous adjustments in prices, consumption, land uses and yields (Nelson et al., 2014). These adjustments can be decomposed into three components. Given the initial equilibrium equation:

$$Q = La_0 Y_0 \tag{26}$$

where $Q$ is total output, $La$ is land, $Y$ stands for yields and 0 denotes an scenario without climate change. Introducing climate change in the model, this model capture its effect through a productivity shock. Thus, the total effect on yields ($\Delta Y_2$) is given by the sum of exogenous and endogenous components ($\Delta Y_{ex} + \Delta Y_{en}$). $Y_{en}$ refers to management adjustments, which include changes in prices that lead to changes in input combinations. Therefore, the level of yields with climate change is as follows:

$$Y_1 = Y_0 + \Delta Y_{ex} + \Delta Y_{en} \tag{27}$$

Here, the expected exogenous effect of climate change on yields is negative while the expected endogenous effect is positive and partially/totally offsets the exogenous harmful effect via adaptation strategies. Consequently, the total output when climate change takes place is as follows:

$$Q_1 = La_1 Y_1 = La_1(Y_0 + \Delta Y_{ex} + \Delta Y_{en}) \tag{28}$$

Recalling equation 26, the net effect of climate change on output is equal to $\Delta Q_1 = Q_0 - Q_1$. Adding more complexity to the model, Hertel (2011) includes a set of equations in the model that captures long run adjustments in the agriculture sector. It includes prices ($P$), supply ($Q$), land area ($La$) and yields ($Y$). The relationship between these variables depends on demand elasticity ($\eta_d$), extensification elasticity ($\eta_E$)[99] and the intensification elasticity ($\eta_I$)[100] and is as follows:

$$\Delta P = \frac{-\Delta Y}{\eta_d + \eta_E + \eta_I} \tag{29}$$

$$\Delta Q = \frac{\Delta Y \eta_d}{\eta_d + \eta_E + \eta_I}$$

$$\Delta La = \frac{-\Delta Y \eta_E}{\eta_d + \eta_E + \eta_I}$$

$$\Delta Q = \frac{\Delta Y(\eta_d + \eta_E)}{\eta_d + \eta_E + \quad {}_I + \Delta Y \eta_E}$$

This setting allows researchers to account for adaptation strategies (endogenous adjustments) in the simulation of the effects of climate change on agriculture. However, the main disadvantage of computable general equilibrium models is that given their complexity, calibration of such models is not straightforward since it requires information about prices, demand, land uses and other variables. The level of data aggregation also limits its applicability to farm-level datasets. We recognise the advantage of computable general equilibrium models over the Ricardian approach in terms of modelling complex systems but the application of the

[99] This is related to the elasticity of land supply and depends on the share of land allocated to production activities.
[100] This elasticity measures land substitutability with respect to other factors of production.

former method is not part of this chapter. This should be part of the further steps of this research.

### *A2.3. Ricardian analyses and climate change*

**Table 2.14 Literature review (empirical studies)**

| Source | Zone | Dep. Var. | Scenarios | Findings |
|---|---|---|---|---|
| 1. Mendelsohn and Nordhaus (1992) | USA (3k counties) | Farm value and revenue (county averages) | The best and worst climate parameters | Higher temperatures and more precipitation in all seasons, except autumn, reduce and increases average farm values, respectively |
| 2. Mendelsohn et al.(1994) | USA (3,000 counties) | Crop land and revenue (county averages) | Uniform: 5ºF and 8% increments | From -5.7 to +1.2 % of value of output |
| 3. Dinar(1998) | India (5,700 districts | Average net revenue per ha. | Uniform: 2º C and 7% increments | From -35 to -12% of net revenue |
| 4. Maddison (2000) | England and Wales (400 farms) | Farmland sale prices per acre | NA | Climate, soil quality and elevation are important attributes of farmland |
| 5. Patton and McErlean (2003) | Northern Ireland (197 farms) | Farmland sale prices per acre | NA | Spatial effects on land prices |
| 6. Mendelsohn and Dinar (2003) | USA (3,000 counties) | Value per acre (averages) | NA | Irrigation can help agriculturalists to adapt to new climatic conditions |
| 7. Reinsborough (2003) | Canada (267 Census divisions) | Farmland value and weight revenue | Uniform: 5 ºF and 8% increments & non-uniform: CGCMI GAX and GG1 | From -5 to +1% of gross farm income and +-6.4% of agricultural revenue |
| 8. Seo et al. (2005) | Sri Lanka (25 districts) | Net revenue per unit of area | CGCM, CSIRO, CCSR, HAD3 and PCM | From -20 to +72% of net revenue |
| 9. Timmins (2006) | Brazil (3,200 municipios) | Average value of land | Uniform: 1 ºC and 1 cm increments | From +0.88 to +13.8% of average land value |
| 10. Kurukulasuriya et al. (2006) | Africa (9,000 farms) | Farm net revenues | NA | The gains for irrigated crops offset the losses for dryland crops and livestock farms, all revenues increase with precipitation |
| 11. Deschenes and Greenstone (2007) | USA (700 farms per county, 2,268 counties) panel | Farmland values | Benchmark climate change and Hadley 2 | Increases in annual profits of $1.3 billion in 2002 dollars (4% of current profits) |
| 12. Kurukulasuriya and Mendelsohn (2007) | Africa (8,400 farms) | Net revenue per ha | CCC, CCSR, PCM | From -21 to -20% of their net revenue |
| 13. Deressa (2007) | Ethiopia (646 farms) | Net revenue per ha | CGM2, HADCM3, PCM | Increasing temperature and decreasing precipitation will damage Ethiopian agriculture |
| 14. Eid et al. (2007) | Egypt (900 farms) | Net and gross revenue per ha | MAGICC/SCENGEN and GCM | Damages on the national production of rice by -11% and soybeans by -28% by 2050 |

| | | | | |
|---|---|---|---|---|
| 15. Jain (2007) | Zambia (1,000 farms) | Net revenue per ha | 4 seasonal scenarios | From -252 to +2.5% of observed mean net revenue |
| 16. Kabubo and Karanja (2007) | Kenya (816 farms) | Net revenue per ha | CCC and GFDL | From -47 to -17% of net revenue |
| 17. Maddison et al. (2007) | Africa (9,000 farms) | Farmers' perceptions of land values | IPCC SERES scenario | From -30.5% (Niger) to -1.3% (Ethiopia) of farm productivity |
| 18. Mano and Nhemachena (2007) | Zimbabwe (500 farms) | Net revenue per ha | SRES models: CGM2, HadCM3, PCM | From -119 to -8% of net revenue per ha |
| 19. Molua and Lambi (2007) | Cameroon (719 farms) | Net revenue per ha | CGM2, CSIRO2, ECHAM, HadCM3, PCM | From -50 to +38% of net revenue per ha |
| 20. Seo and Mendelsohn (2007) | South America (2,300 farms) | Land value and net revenue per ha | CCC, CCSR, PCM | From -65 to +104% of land value and net revenue per ha |
| 21. Seo and Mendelsohn (2008b) | Africa (5,000 livestock farms) | Net revenues per animal | CCC, CCSR, PCM | From -77 to +34% of expected income |
| 22. Seo and Mendelsohn (2008c) | South America (2,000 farms) | Land value per ha | CCC, CCSR, PCM | From -12 to -53% of their income |
| 23. Fleischer et al. (2008) | Israel (230 farms) | Net revenues per ha | CCC, CCSR, PCM | From -108 to +1,337 dlls. of net profits per ha |
| 24. Seo and Mendelsohn (2008a) | Africa (8,400 farms) | Net revenues per ha | CCC, CCSR, PCM | From -967 to +604 USD/yr/ha of conditional net revenue |
| 25. Seo and Mendelsohn (2008b) | Africa (5,000 livestock farms) | Net revenues per animal | CCC, CCSR, PCM | From -25 to +168 % of expected income per farm |
| 26. Wang (2008) | China (8,400 farms) | Net crop revenues per ha | NA | The likely gains of some farmers will nearly offset losses that will damage other farms in China |
| 27. Deressa and Hassan (2009) | Ethiopia (550 farms) | Net revenues per ha | CGM2, HADCM3, PCM | From -418 to +15.4% of net revenue per hectare |
| 28. Garcia and Viladrich-Grau (2009) | Spain (47 provinces*17 years) | Log average land price per ha | Predicted values 2010-2049 | (SUR model) Price of rain-fed land tends to increase but acreage decrease and mixed results for irrigated land |
| 29. Kabubo-Mariara (2009) | Kenya (722 livestock farms) | Net revenues per farm (livestock) | CGCM2, CSIRO2, ECHAM, HADCM3, PCM | From -169 to -6% of farm net revenue |
| 30. Seo et al. (2009) | Africa (8,500 farms) | net revenues per ha | CCC, PCM | From -169 to +121% of the farm net revenue |
| 31. Maddison (2009) | England and Wales (507 farms) | Log price per acre | NA | The existence of spatial effects |
| 32. Mendelsohn et al. (2010) | Mexico (621 farms) | Log land value per ha | PCM, MIMR, HAD | From -62 to -39% of land value per ha |
| 33. Massetti and Mendelsohn (2011) | USA (2,900 counties) Panel | Average estimated value of land per ha | Uniform: 2.7o C and 8% increments | From -5 to +12% of land value per ha |
| 34. Ater and Aye (2012) | Nigeria (maize farms) | Net revenues per ha | CGM2, HADCM3, PCM | From -42 to +63% of net revenue |

| | | | | |
|---|---|---|---|---|
| 35. Di Falco et al. (2012) | Nile Basin Ethiopia (939 farms) | Quantity per ha and revenue | NA | Adaptation plays an important role |
| 36. Van Passel et al. (2017) | Europe (37,600 farms) | Land value per ha | HadCM3, ECHO-G, NCAR PCM | From -4,971 to -861 Euro per ha of land value |
| 37. Fezzi and Bateman (2015) | Great Britain (2.5k farms*10 years) | Land value per ha | Models A, B, C, D | From -20 to +70% of land value |
| 38. Gebreegziabher et al. (2013) | Nile Basin Ethiopia (952 farms) | Net revenue | PCM, HadCM3, CGCM2 | From -217 to +188% of net revenue |
| 39 Xin et al. (2013) | (9,000 farms) | Rural household output | CNCC | From -0.31 to -2.69% in 2030 and from -1.93 to -3.07% in 2050 |
| 40. Bezabih et al. (2014) | Ethiopia (1,500 farms) | Crop and farm revenue | NA | Temperature effects are non-linear, but only when the weather measures are combined with the extreme tails of the distribution of climate measures |
| 41. Wang et al. (2014) | China (8,400 farms) | Crop net revenue per ha | NA | Warming will harm farms both in the north and south of China |
| 42. Mendelsohn (2014) | Asia (8,400 farms) | Crop net revenue per ha | NA | From -28 to +3% of crop net revenue |

Source: literature review

### *A2.4. Soil types*

Acrisol or acid soil is utilised for agriculture with very low yields, nonetheless, it is suitable for some commodities such as cacao, pineapple or coffee, which show medium or high yields. Regarding livestock, acrisoles are suitable for pastures. Andosol or black soil has a volcanic origin. Agriculture yields are generally low because this soil contains high levels of phosphor. Nevertheless, with adequate levels of fertilization, avocado plantations in Michoacan observe high productivity levels. Arenosol or sandy soil is not permeable and has low capacity to hold water and nutrients.

Cambisol or changing soil. The uses and yields of this soil depend on climate conditions. Castanozem or brown alkaline soil holds high levels of nutrients and organic matter. In Mexico, this soil is utilised for extensive livestock activities showing medium-high yields. Regarding arable activities, it is suitable for grains, oilseeds and vegetables, and, if the farmer irrigates, its productivity increases due to its high level of natural fertility. Chernozem or black soil has high levels of nutrients and organic matter. This soil is more fertile than castanozems.

Feozem or brown soil is rich in nutrients and organic matter. It is similar to chernozems and catanozems, but it does not have layers of lime. The deeper feozems are suitable for both rain-fed and irrigated lands that cultivate grains, legumes and vegetables (high yields). The shallow feozems are suitable for grazing and they show low levels of crop yields. Fluvisol or river soil. For agriculture purposes, the molic and calcaric fluvisols are more suitable due to their level of nutrients. Gleysol or swampy soil observes water concentration within the 50 cm. of depth. Regarding livestock, this soil is utilised for beef cattle production with moderate to high yields. For agriculture purposes, rice and sugar cane show high yields because these crops are flood tolerant.

The natural fertility of Litosol or stone soil depends on climate factors. In terms of agriculture, it is suitable for the production of maize and 'nopal' (cactus). Luvisol or soil with clay accumulation is associated to medium levels of agricultural yields. This soil is suitable for coffee, fruits, avocado and livestock. Nitosol or bright soil is suitable for the production of tobacco and beef cattle (through cultivated pastures). Planosol or plain soil enables the production of beef cattle, sheep and goats, which show moderate yields. Ranker or soils with steep slope, high acidity and high levels of organic matter. These soils mostly appear in forestry areas. Regosol or soil that covers stones. The level or organic matter in regosols is low. In coastal zones, coconut and watermelon production observe high yields.

Rendzina or noisy soil is rich on organic matter and, consequently, shows a high level of fertility. In Yucatan, it is used for the production of sisal (high yields) and maize (low yields). Solonchak or saline soil permits the production of agricultural commodities that are salt resistant. Solonetz or high salt concentrations soil is located in zones where the alkali sodium concentration is high. Its vegetation is scarce, and if it exists, it comprises pastures and bushes. It is not suitable for farming activities.

Vertisol or stirred soil is part of the main irrigation districts in Sinaloa, Guanajuato, Sonora, Jalisco, Tamaulipas and Veracruz. It is very fertile, but its hardness limits tillage activities. This type of soil is suitable for the production of sugar cane, cereals, vegetables and cotton. Xerosol or dry soil is part of arid and semi-arid zones at the north and center of Mexico. It has a white superficial layer because the low level of organic matter. The agriculture yields of this profile depend on water availability for irrigation. This soil is suitable for livestock, especially in Coahuila, Chihuahua and Nuevo Leon. Yermosol or desert soil characterises most of the arid zones in Mexico such as Los Llanos de la Magdalena, the Sierra de la Giganta in Baja California Sur, plains in Sonora, the Bolson de Mapimi and the Sierra de la Paila in Coahuila. When water and irrigation technology are available, yields are very high. The most common cultivated products are ‘candelilla’, ‘nopal’ and ‘lechuguilla’

### *A2.5. Descriptive statistics and additional regressions*

## Table 2.15 Descriptive statistics of 2012 and 2014 samples (all farms)

| Variable | 2012 | | | | | | | | 2014 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Net revenues | | | | Rental prices | | | | Net revenues | | | | Rental prices | | | |
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| *Net Rev. per ha*$1000* | 6.18 | 20.76 | -52.99 | 191.92 | | | | | -5.42 | 27.89 | -159.98 | 217.32 | | | | |
| *Rent per ha*$1000* | | | | | 6.39 | 6.15 | 0.05 | 53.58 | | | | | 5.07 | 5.52 | 0.04 | 44.44 |
| *Temp. Sp-Su (ºC)* | 23.63 | 3.77 | 11.50 | 30.62 | 24.21 | 3.55 | 12.08 | 30.39 | 22.64 | 4.36 | 8.83 | 30.62 | 23.33 | 3.97 | 10.55 | 30.57 |
| *Temp. Au-Wi (ºC)* | 19.13 | 4.65 | 7.75 | 28.64 | 19.78 | 4.17 | 8.40 | 27.89 | 18.80 | 4.63 | 6.71 | 28.66 | 19.04 | 4.27 | 8.41 | 28.17 |
| *Rain. Sp-Su (mm.)* | 4.74 | 3.11 | 0.16 | 27.40 | 3.38 | 2.26 | 0.16 | 13.28 | 5.75 | 3.45 | 0.12 | 27.91 | 4.26 | 2.93 | 0.16 | 24.72 |
| *Rain. Au-Wi (mm.)* | 3.33 | 2.96 | 0.36 | 24.46 | 2.13 | 1.18 | 0.36 | 14.53 | 3.70 | 2.97 | 0.36 | 24.51 | 2.49 | 1.84 | 0.36 | 24.46 |
| *Storms Sp-Su (days)* | 5.31 | 7.47 | 0.00 | 93.66 | 4.12 | 5.80 | 0.00 | 47.04 | 6.09 | 7.90 | 0.00 | 93.66 | 4.82 | 6.20 | 0.00 | 49.35 |
| *Storms Au-Wi (days)* | 2.79 | 4.74 | 0.00 | 62.16 | 2.10 | 3.80 | 0.00 | 63.62 | 3.11 | 4.59 | 0.00 | 63.62 | 2.51 | 3.83 | 0.00 | 50.51 |
| *Clouds Sp-Su (days)* | 37.55 | 18.67 | 0.00 | 150.58 | 34.25 | 18.54 | 0.00 | 144.52 | 39.85 | 19.00 | 0.00 | 150.58 | 35.74 | 19.21 | 0.00 | 149.21 |
| *Clouds Au-Wi (days)* | 36.09 | 19.53 | 0.00 | 146.61 | 29.37 | 13.78 | 0.00 | 138.87 | 37.00 | 19.78 | 0.00 | 146.61 | 30.73 | 15.34 | 0.00 | 140.28 |
| *Acrisol (%)* | 1.65 | 11.43 | 0.00 | 100.00 | 0.38 | 5.10 | 0.00 | 100.00 | 2.38 | 13.57 | 0.00 | 100.00 | 0.98 | 8.56 | 0.00 | 100.00 |
| *Andosol (%)* | 0.94 | 9.10 | 0.00 | 100.00 | 0.55 | 6.99 | 0.00 | 100.00 | 3.56 | 17.06 | 0.00 | 100.00 | 1.41 | 10.93 | 0.00 | 100.00 |
| *Arenosol (%)* | 0.04 | 1.81 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 1.73 | 0.00 | 100.00 | 0.02 | 1.34 | 0.00 | 100.00 |
| *Cambisol (%)* | 7.15 | 22.68 | 0.00 | 100.00 | 7.40 | 22.71 | 0.00 | 100.00 | 9.18 | 25.39 | 0.00 | 100.00 | 8.68 | 24.71 | 0.00 | 100.00 |
| *Catanozem (%)* | 2.60 | 14.34 | 0.00 | 100.00 | 1.16 | 9.40 | 0.00 | 100.00 | 2.21 | 13.22 | 0.00 | 100.00 | 1.02 | 8.94 | 0.00 | 100.00 |
| *Chernozem (%)* | 0.06 | 1.49 | 0.00 | 100.00 | 0.03 | 1.61 | 0.00 | 83.33 | 0.03 | 1.15 | 0.00 | 100.00 | 0.02 | 1.13 | 0.00 | 80.00 |
| *Feozem (%)* | 12.89 | 29.12 | 0.00 | 100.00 | 10.69 | 26.77 | 0.00 | 100.00 | 15.98 | 32.36 | 0.00 | 100.00 | 16.18 | 32.88 | 0.00 | 100.00 |
| *Fluvisol (%)* | 0.32 | 4.07 | 0.00 | 100.00 | 0.39 | 3.82 | 0.00 | 80.00 | 0.29 | 4.20 | 0.00 | 100.00 | 0.34 | 3.85 | 0.00 | 100.00 |
| *Gleysol (%)* | 2.12 | 13.50 | 0.00 | 100.00 | 0.03 | 1.26 | 0.00 | 64.73 | 1.65 | 12.11 | 0.00 | 100.00 | 0.14 | 3.40 | 0.00 | 100.00 |
| *Litosol (%)* | 5.16 | 17.18 | 0.00 | 100.00 | 2.06 | 9.62 | 0.00 | 100.00 | 6.02 | 19.07 | 0.00 | 100.00 | 2.44 | 11.47 | 0.00 | 100.00 |
| *Luvisol (%)* | 3.49 | 15.93 | 0.00 | 100.00 | 2.07 | 12.31 | 0.00 | 100.00 | 5.42 | 19.96 | 0.00 | 100.00 | 2.61 | 13.93 | 0.00 | 100.00 |
| *Nitosol (%)* | 0.21 | 4.15 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.26 | 4.60 | 0.00 | 100.00 | 0.06 | 2.40 | 0.00 | 100.00 |
| *Planosol (%)* | 3.28 | 16.25 | 0.00 | 100.00 | 3.39 | 16.75 | 0.00 | 100.00 | 2.39 | 13.85 | 0.00 | 100.00 | 2.89 | 15.35 | 0.00 | 100.00 |
| *Ranker (%)* | 0.01 | 0.34 | 0.00 | 37.12 | 0.00 | 0.04 | 0.00 | 1.81 | 0.00 | 0.16 | 0.00 | 37.06 | 0.00 | 0.06 | 0.00 | 2.98 |
| *Regosol (%)* | 12.42 | 27.69 | 0.00 | 100.00 | 10.07 | 26.62 | 0.00 | 100.00 | 13.16 | 29.52 | 0.00 | 100.00 | 12.90 | 29.92 | 0.00 | 100.00 |
| *Rendzina (%)* | 5.85 | 21.13 | 0.00 | 100.00 | 0.71 | 6.46 | 0.00 | 100.00 | 5.61 | 20.77 | 0.00 | 100.00 | 1.65 | 10.65 | 0.00 | 100.00 |
| *Solonchak (%)* | 2.17 | 11.52 | 0.00 | 100.00 | 3.36 | 13.46 | 0.00 | 100.00 | 1.23 | 8.69 | 0.00 | 100.00 | 2.19 | 11.27 | 0.00 | 100.00 |
| *Solonets (%)* | 0.06 | 1.22 | 0.00 | 50.61 | 0.00 | 0.08 | 0.00 | 4.38 | 0.02 | 0.76 | 0.00 | 100.00 | 0.02 | 0.77 | 0.00 | 37.50 |
| *Vertisol (%)* | 21.80 | 38.11 | 0.00 | 100.00 | 35.40 | 43.37 | 0.00 | 100.00 | 18.81 | 35.98 | 0.00 | 100.00 | 29.11 | 41.80 | 0.00 | 100.00 |
| *Xerosol (%)* | 15.56 | 32.55 | 0.00 | 100.00 | 21.02 | 37.41 | 0.00 | 100.00 | 10.67 | 28.29 | 0.00 | 100.00 | 16.16 | 34.04 | 0.00 | 100.00 |
| *Yermosol (%)* | 2.25 | 12.63 | 0.00 | 100.00 | 1.29 | 9.18 | 0.00 | 100.00 | 1.10 | 9.23 | 0.00 | 100.00 | 1.19 | 9.31 | 0.00 | 100.00 |
| *Total area*$1000* | 0.47 | 1.95 | 0.00 | 76.29 | | | | | 0.11 | 0.99 | 0.00 | 116.47 | | | | |
| *Rented area*$1000* | | | | | 0.08 | 0.19 | 0.00 | 4.01 | | | | | 0.05 | 0.17 | 0.00 | 7.05 |
| *Arable area*$1000* | 0.08 | 0.18 | 0.00 | 5.71 | 0.11 | 0.19 | 0.00 | 4.09 | 0.03 | 0.10 | 0.00 | 7.01 | 0.04 | 0.15 | 0.00 | 7.01 |
| *City (km)* | 12.82 | 13.33 | 0.00 | 134.91 | 7.27 | 7.81 | 0.03 | 71.33 | 9.58 | 10.46 | 0.00 | 138.18 | 7.21 | 8.16 | 0.00 | 74.51 |
| *Water body (km)* | 29.02 | 27.11 | 0.02 | 276.10 | 22.21 | 20.67 | 0.08 | 244.48 | 30.07 | 25.87 | 0.00 | 275.59 | 24.80 | 20.82 | 0.05 | 253.09 |
| *River (km)* | 23.17 | 39.00 | 0.01 | 319.21 | 16.26 | 26.35 | 0.04 | 289.68 | 19.64 | 35.81 | 0.00 | 344.20 | 15.13 | 25.81 | 0.00 | 290.81 |
| *Road density (m/km)* | 228.28 | 204.53 | 5.00 | 2419.08 | 264.58 | 204.86 | 25.19 | 1,801.76 | 329.45 | 266.91 | 7.65 | 2057.29 | 314.64 | 254.20 | 16.20 | 2,057.29 |
| *Irrigation (%)* | 43.24 | 46.34 | 0.00 | 100.00 | 77.18 | 38.31 | 0.00 | 100.00 | 30.06 | 43.85 | 0.00 | 100.00 | 58.01 | 48.14 | 0.00 | 100.00 |
| *Ejidal (%)* | 37.96 | 46.17 | 0.00 | 100.00 | 61.68 | 45.21 | 0.00 | 100.00 | 57.46 | 47.76 | 0.00 | 100.00 | 60.88 | 46.56 | 0.00 | 100.00 |
| *Electricity (1=yes)* | 0.40 | 0.49 | 0.00 | 1.00 | 0.39 | 0.49 | 0.00 | 1.00 | 0.18 | 0.39 | 0.00 | 1.00 | 0.26 | 0.44 | 0.00 | 1.00 |
| *Observations* | 17,351 | | | | 2,695 | | | | 58,743 | | | | 5,596 | | | |

Source: NAS-2012 and NAS-2014 (INEGI, 2012; INEGI, 2014)

## Table 2.16 Descriptive statistics of 2012 and 2014 samples (farms reporting net revenues and rental prices)

| Variable | 2012 | | | | | | | | 2014 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Net revenues | | | | Rental prices | | | | Net revenues | | | | Rental prices | | | |
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| *Net Rev. per ha*$1000* | 9.53 | 21.18 | -52.99 | 178.59 | | | | | -3.83 | 29.88 | -159.98 | 216.45 | | | | |
| *Rent per ha*$1000* | | | | | 5.93 | 5.39 | 0.05 | 53.58 | | | | | 4.88 | 5.19 | 0.04 | 44.44 |
| *Temp. Sp-Su (ºC)* | 24.25 | 3.54 | 12.08 | 30.37 | 24.26 | 3.54 | 12.08 | 30.39 | 23.38 | 3.99 | 10.55 | 30.28 | 23.38 | 3.98 | 10.55 | 30.57 |
| *Temp. Au-Wi (ºC)* | 19.77 | 4.19 | 8.26 | 27.88 | 19.78 | 4.20 | 8.40 | 27.89 | 19.05 | 4.31 | 8.41 | 27.96 | 19.06 | 4.31 | 8.41 | 27.96 |
| *Rain. Sp-Su (mm.)* | 335.08 | 224.58 | 15.78 | 1330.45 | 3.35 | 2.24 | 0.16 | 13.28 | 4.23 | 2.93 | 0.16 | 24.72 | 4.23 | 2.93 | 0.16 | 24.72 |
| *Rain. Au-Wi (mm.)* | 212.09 | 118.88 | 36.56 | 1462.41 | 2.12 | 1.18 | 0.36 | 14.53 | 2.49 | 1.85 | 0.36 | 24.46 | 2.49 | 1.85 | 0.36 | 24.46 |
| *Storms Sp-Su (days)* | 4.09 | 5.64 | 0.00 | 46.94 | 4.10 | 5.76 | 0.00 | 47.04 | 4.73 | 6.07 | 0.00 | 49.35 | 4.73 | 6.11 | 0.00 | 49.35 |
| *Storms Au-Wi (days)* | 2.07 | 3.60 | 0.00 | 49.26 | 2.09 | 3.67 | 0.00 | 48.38 | 2.49 | 3.78 | 0.00 | 48.99 | 2.49 | 3.85 | 0.00 | 50.51 |
| *Clouds Sp-Su (days)* | 34.23 | 18.53 | 0.00 | 142.90 | 34.27 | 18.74 | 0.00 | 144.52 | 35.30 | 18.85 | 0.00 | 149.21 | 35.40 | 19.01 | 0.00 | 149.21 |
| *Clouds Au-Wi (days)* | 29.51 | 13.84 | 0.00 | 137.59 | 29.56 | 13.99 | 0.00 | 138.87 | 30.60 | 15.16 | 0.00 | 140.28 | 30.66 | 15.31 | 0.00 | 140.28 |
| *Acrisol (%)* | 0.34 | 4.30 | 0.00 | 89.06 | 0.38 | 5.00 | 0.00 | 100.00 | 1.03 | 8.85 | 0.00 | 100.00 | 1.04 | 8.79 | 0.00 | 100.00 |
| *Andosol (%)* | 0.53 | 6.90 | 0.00 | 100.00 | 0.54 | 7.02 | 0.00 | 100.00 | 1.38 | 10.80 | 0.00 | 100.00 | 1.33 | 10.70 | 0.00 | 100.00 |
| *Arenosol (%)* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 1.37 | 0.00 | 100.00 | 0.02 | 1.37 | 0.00 | 100.00 |
| *Cambisol (%)* | 7.36 | 22.23 | 0.00 | 100.00 | 7.47 | 22.81 | 0.00 | 100.00 | 8.78 | 24.47 | 0.00 | 100.00 | 8.86 | 24.90 | 0.00 | 100.00 |
| *Catanozem (%)* | 1.17 | 9.12 | 0.00 | 100.00 | 1.27 | 9.90 | 0.00 | 100.00 | 1.03 | 8.86 | 0.00 | 100.00 | 1.04 | 9.03 | 0.00 | 100.00 |
| *Chernozem (%)* | 0.00 | 0.06 | 0.00 | 3.10 | 0.00 | 0.06 | 0.00 | 3.10 | 0.02 | 1.31 | 0.00 | 94.05 | 0.02 | 1.12 | 0.00 | 80.00 |
| *Feozem (%)* | 10.04 | 25.34 | 0.00 | 100.00 | 10.10 | 25.93 | 0.00 | 100.00 | 15.66 | 31.82 | 0.00 | 100.00 | 15.85 | 32.56 | 0.00 | 100.00 |
| *Fluvisol (%)* | 0.43 | 4.07 | 0.00 | 80.00 | 0.40 | 3.89 | 0.00 | 80.00 | 0.34 | 3.89 | 0.00 | 100.00 | 0.33 | 3.85 | 0.00 | 100.00 |
| *Gleysol (%)* | 0.04 | 1.35 | 0.00 | 64.73 | 0.03 | 1.33 | 0.00 | 64.73 | 0.13 | 3.30 | 0.00 | 100.00 | 0.14 | 3.49 | 0.00 | 100.00 |
| *Litosol (%)* | 2.11 | 9.79 | 0.00 | 100.00 | 2.02 | 9.44 | 0.00 | 100.00 | 2.57 | 11.64 | 0.00 | 100.00 | 2.46 | 11.47 | 0.00 | 100.00 |
| *Luvisol (%)* | 2.22 | 12.60 | 0.00 | 100.00 | 2.25 | 12.87 | 0.00 | 100.00 | 2.58 | 13.58 | 0.00 | 100.00 | 2.59 | 13.83 | 0.00 | 100.00 |
| *Nitosol (%)* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.07 | 2.46 | 0.00 | 100.00 | 0.07 | 2.46 | 0.00 | 100.00 |
| *Planosol (%)* | 3.62 | 16.74 | 0.00 | 100.00 | 3.64 | 17.36 | 0.00 | 100.00 | 2.98 | 15.40 | 0.00 | 100.00 | 2.95 | 15.56 | 0.00 | 100.00 |
| *Ranker (%)* | 0.00 | 0.02 | 0.00 | 1.03 | 0.00 | 0.04 | 0.00 | 1.81 | 0.00 | 0.05 | 0.00 | 2.61 | 0.00 | 0.06 | 0.00 | 2.98 |
| *Regosol (%)* | 9.78 | 25.91 | 0.00 | 100.00 | 9.61 | 26.06 | 0.00 | 100.00 | 13.14 | 29.82 | 0.00 | 100.00 | 13.10 | 30.08 | 0.00 | 100.00 |
| *Rendzina (%)* | 0.75 | 6.52 | 0.00 | 100.00 | 0.75 | 6.66 | 0.00 | 100.00 | 1.63 | 10.38 | 0.00 | 100.00 | 1.64 | 10.61 | 0.00 | 100.00 |
| *Solonchak (%)* | 3.66 | 13.86 | 0.00 | 100.00 | 3.56 | 13.91 | 0.00 | 100.00 | 2.16 | 10.86 | 0.00 | 100.00 | 2.21 | 11.34 | 0.00 | 100.00 |
| *Solonets (%)* | 0.00 | 0.09 | 0.00 | 4.38 | 0.00 | 0.09 | 0.00 | 4.38 | 0.02 | 0.67 | 0.00 | 37.50 | 0.02 | 0.80 | 0.00 | 37.50 |
| *Vertisol (%)* | 35.68 | 42.94 | 0.00 | 100.00 | 35.84 | 43.44 | 0.00 | 100.00 | 28.87 | 41.25 | 0.00 | 100.00 | 28.78 | 41.60 | 0.00 | 100.00 |
| *Xerosol (%)* | 21.07 | 37.00 | 0.00 | 100.00 | 20.94 | 37.29 | 0.00 | 100.00 | 16.37 | 33.91 | 0.00 | 100.00 | 16.39 | 34.20 | 0.00 | 100.00 |
| *Yermosol (%)* | 1.21 | 8.58 | 0.00 | 100.00 | 1.21 | 8.76 | 0.00 | 100.00 | 1.22 | 9.32 | 0.00 | 100.00 | 1.16 | 9.21 | 0.00 | 100.00 |
| *Total area*$1000* | 0.15 | 0.32 | 0.00 | 6.14 | | | | | 0.09 | 0.22 | 0.00 | 7.05 | | | | |
| *Rented area*$1000* | | | | | 0.08 | 0.20 | 0.00 | 4.01 | | | | | 0.05 | 0.17 | 0.00 | 7.05 |
| *Arable area*$1000* | 0.11 | 0.19 | 0.00 | 4.09 | 0.11 | 0.19 | 0.00 | 4.09 | 0.07 | 0.18 | 0.00 | 7.01 | 0.04 | 0.15 | 0.00 | 7.01 |
| *City (km)* | 7.57 | 7.98 | 0.27 | 71.33 | 7.47 | 8.01 | 0.03 | 71.33 | 7.39 | 8.25 | 0.00 | 74.51 | 7.32 | 8.25 | 0.00 | 74.51 |
| *Water body (km)* | 21.43 | 18.80 | 0.22 | 169.78 | 21.39 | 18.90 | 0.08 | 169.78 | 24.68 | 20.41 | 0.29 | 244.48 | 24.66 | 20.36 | 0.05 | 244.48 |
| *River (km)* | 15.33 | 23.57 | 0.04 | 289.15 | 15.25 | 23.63 | 0.04 | 289.68 | 14.88 | 24.78 | 0.02 | 264.39 | 14.86 | 24.73 | 0.00 | 271.08 |
| *Road density (m/km)* | 257.94 | 197.60 | 25.19 | 1801.76 | 257.94 | 197.60 | 25.19 | 1,801.76 | 309.63 | 251.26 | 16.20 | 2057.29 | 309.63 | 251.26 | 16.20 | 2,057.29 |
| *Irrigation (%)* | 76.39 | 38.76 | 0.00 | 100.00 | 76.39 | 38.76 | 0.00 | 100.00 | 58.22 | 46.85 | 0.00 | 100.00 | 57.95 | 48.13 | 0.00 | 100.00 |
| *Ejidal (%)* | 59.38 | 43.35 | 0.00 | 100.00 | 62.58 | 45.01 | 0.00 | 100.00 | 59.68 | 44.62 | 0.00 | 100.00 | 61.29 | 46.43 | 0.00 | 100.00 |
| *Electricity (1=yes)* | 0.35 | 0.48 | 0.00 | 1.00 | 0.35 | 0.48 | 0.00 | 1.00 | 0.25 | 0.43 | 0.00 | 1.00 | 0.25 | 0.43 | 0.00 | 1.00 |
| *Observations* | 2,388 | | | | 2,388 | | | | 5,301 | | | | 5,301 | | | |

Source: NAS-2012 and NAS-2014 (INEGI, 2012; INEGI, 2014)

## Table 2.17 Ricardian model using quarterly climate (all farms-non demeaned)

| | | 2012 | | | 2014 | | | 2012 | | | 2014 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| | | **Climate** | | | **Climate** | | | **Climate** | | | **Climate** | |
| *Temp. spring* | -0.1514 | -0.8962 | -0.2016 | -1.1088*** | -1.4421*** | -1.3108*** | 0.0623 | -0.6031** | -0.3048 | 0.8176*** | 0.3035* | 0.3768* |
| | (0.5285) | (0.5563) | (0.6601) | (0.2675) | (0.2789) | (0.3262) | (0.3105) | (0.2858) | (0.3786) | (0.1780) | (0.1635) | (0.2010) |
| *Temp. spring sq.* | 0.0075 | 0.0177 | -0.0036 | 0.0123** | 0.0197*** | 0.0156** | -0.0070 | 0.0074 | 0.0065 | -0.0219*** | -0.0104*** | -0.0097** |
| | (0.0115) | (0.0120) | (0.0143) | (0.0057) | (0.0059) | (0.0066) | (0.0068) | (0.0062) | (0.0083) | (0.0038) | (0.0034) | (0.0041) |
| *Temp. summer* | 3.8269*** | 2.1007*** | 2.5729*** | 2.6003*** | 2.4582*** | 2.0405*** | 0.7839* | 1.0816*** | 0.4547 | -0.1555 | -1.0469*** | -0.8958*** |
| | (0.7863) | (0.8088) | (0.9133) | (0.3564) | (0.3651) | (0.4435) | (0.4047) | (0.3748) | (0.4754) | (0.2191) | (0.2084) | (0.2588) |
| *Temp. summer sq.* | -0.0779*** | -0.0580*** | -0.0673*** | -0.0318*** | -0.0286*** | -0.0198** | -0.0127* | -0.0188*** | -0.0103 | 0.0020 | 0.0145*** | 0.0117*** |
| | (0.0131) | (0.0136) | (0.0159) | (0.0059) | (0.0062) | (0.0077) | (0.0065) | (0.0062) | (0.0083) | (0.0033) | (0.0033) | (0.0043) |
| *Temp. autumn* | -2.8516*** | 1.1147 | -0.0443 | -1.4393*** | -1.6396*** | -1.3845** | -0.7215* | -0.4137 | -0.3137 | 0.1062 | 1.7700*** | 0.8434*** |
| | (0.9211) | (0.9815) | (1.1485) | (0.4693) | (0.4813) | (0.6073) | (0.4277) | (0.3953) | (0.5088) | (0.2642) | (0.2518) | (0.3253) |
| *Temp. autumn sq.* | 0.0867*** | 0.0138 | 0.0448* | 0.0242*** | 0.0217** | 0.0115 | 0.0167** | 0.0112 | 0.0109 | 0.0016 | -0.0274*** | -0.0078 |
| | (0.0172) | (0.0185) | (0.0229) | (0.0089) | (0.0092) | (0.0122) | (0.0074) | (0.0071) | (0.0098) | (0.0044) | (0.0044) | (0.0061) |
| *Temp. winter* | 0.1973 | -0.8012* | -0.9716** | 0.4214* | 1.0314*** | 0.6282** | 0.2705 | 0.3106 | 0.3330 | -0.1925 | -0.7855*** | -0.2230 |
| | (0.4423) | (0.4622) | (0.4943) | (0.2463) | (0.2511) | (0.2874) | (0.2291) | (0.2134) | (0.2653) | (0.1506) | (0.1447) | (0.1618) |
| *Temp. winter sq.* | -0.0182* | 0.0085 | 0.0076 | -0.0032 | -0.0143** | 0.0026 | -0.0040 | -0.0055 | -0.0095 | 0.0071** | 0.0186*** | 0.0011 |
| | (0.0103) | (0.0109) | (0.0127) | (0.0055) | (0.0057) | (0.0070) | (0.0056) | (0.0051) | (0.0073) | (0.0034) | (0.0033) | (0.0040) |
| *Rain. spring* | 1.7325 | -0.6928 | -5.0727** | 0.0871 | 1.4755*** | 0.5549 | 0.7196 | 1.3714 | 1.7921 | -0.4303 | -1.0034*** | -1.2975*** |
| | (1.4204) | (1.4515) | (1.9739) | (0.5286) | (0.5455) | (0.6762) | (0.9230) | (0.9061) | (1.4287) | (0.3826) | (0.3600) | (0.4738) |
| *Rain. spring sq.* | -0.8231*** | -0.8294*** | -0.6185*** | 0.1634*** | 0.1405*** | 0.0101 | -0.2332 | -0.0037 | -0.3196 | -0.0501 | -0.0108 | 0.0033 |
| | (0.1107) | (0.1151) | (0.1258) | (0.0447) | (0.0454) | (0.0516) | (0.1652) | (0.1747) | (0.2463) | (0.0364) | (0.0299) | (0.0330) |
| *Rain. summer* | 4.0885*** | 2.1251*** | -0.7370 | 1.1245*** | 0.8788*** | -0.0284 | 0.1042 | 0.3829 | 0.6791* | 0.1438 | -0.0442 | -0.0787 |
| | (0.5475) | (0.5767) | (0.6719) | (0.1951) | (0.1989) | (0.2302) | (0.3386) | (0.3061) | (0.3681) | (0.1384) | (0.1316) | (0.1537) |
| *Rain. summer sq.* | -0.0335*** | -0.0204* | -0.0050 | -0.0128*** | -0.0257*** | -0.0019 | 0.0223** | 0.0230** | 0.0111 | 0.0083** | 0.0080** | 0.0094*** |
| | (0.0111) | (0.0117) | (0.0127) | (0.0046) | (0.0048) | (0.0051) | (0.0098) | (0.0100) | (0.0111) | (0.0035) | (0.0034) | (0.0034) |
| *Rain. autumn* | -2.0571** | 0.4198 | 3.8284*** | 0.1158 | -0.6176** | 1.0463*** | 0.0357 | 0.1859 | -0.9023 | -0.1387 | 0.4811** | -0.1401 |
| | (0.8477) | (0.8898) | (1.0066) | (0.3007) | (0.3103) | (0.3616) | (0.5752) | (0.5360) | (0.6486) | (0.2215) | (0.2034) | (0.2400) |
| *Rain. autumn sq.* | 0.1307*** | 0.1014*** | 0.0847*** | -0.0425*** | -0.0309** | -0.0509*** | -0.0836** | -0.0548* | 0.0412 | -0.0084 | -0.0236*** | -0.0180* |
| | (0.0260) | (0.0265) | (0.0284) | (0.0140) | (0.0142) | (0.0155) | (0.0324) | (0.0325) | (0.0395) | (0.0091) | (0.0090) | (0.0094) |
| *Rain. winter* | -2.0707** | -1.5585 | -0.8973 | -1.9464*** | -0.7081 | -1.6931*** | -2.0732*** | -2.2398*** | -0.6715 | -0.0082 | -1.0616*** | 0.7205 |
| | (0.9607) | (0.9815) | (1.1030) | (0.4667) | (0.4718) | (0.5546) | (0.7888) | (0.5694) | (0.7229) | (0.3971) | (0.3579) | (0.4421) |
| *Rain. winter sq.* | -0.0248 | -0.1344** | -0.2211*** | 0.1140*** | 0.0513 | 0.1614*** | 0.6948*** | 0.3451** | 0.1630 | 0.0820** | 0.0570* | 0.0760*** |
| | (0.0588) | (0.0601) | (0.0651) | (0.0366) | (0.0382) | (0.0426) | (0.1781) | (0.1711) | (0.2112) | (0.0401) | (0.0326) | (0.0293) |
| *Temp. sp*Rain. sp* | 0.0458 | 0.1665*** | 0.2953*** | -0.0176 | -0.0676*** | 0.0080 | 0.0091 | -0.0273 | -0.0213 | 0.0219 | 0.0447*** | 0.0477*** |
| | (0.0529) | (0.0547) | (0.0739) | (0.0218) | (0.0227) | (0.0270) | (0.0355) | (0.0351) | (0.0575) | (0.0143) | (0.0135) | (0.0177) |
| *Temp. su*Rain. su* | -0.1299*** | -0.0648*** | 0.0419* | -0.0192*** | -0.0013 | 0.0161* | -0.0124 | -0.0229** | -0.0343*** | -0.0128*** | -0.0035 | -0.0052 |
| | (0.0200) | (0.0208) | (0.0242) | (0.0071) | (0.0075) | (0.0087) | (0.0112) | (0.0100) | (0.0123) | (0.0047) | (0.0044) | (0.0052) |
| *Temp. au*Rain. au* | 0.0426 | -0.0581 | -0.2068*** | -0.0193 | 0.0095 | -0.0455*** | 0.0131 | -0.0016 | 0.0283 | 0.0060 | -0.0155** | 0.0158* |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (0.0341) | (0.0361) | (0.0419) | (0.0121) | (0.0128) | (0.0158) | (0.0202) | (0.0187) | (0.0239) | (0.0081) | (0.0073) | (0.0088) |
| *Temp. wi*Rain. wi* | 0.0364 | 0.0638 | 0.0935* | 0.1292*** | 0.0777*** | 0.0870*** | 0.0179 | 0.0750** | -0.0027 | -0.0075 | 0.0576*** | -0.0456** |
| | (0.0427) | (0.0445) | (0.0525) | (0.0223) | (0.0230) | (0.0291) | (0.0451) | (0.0321) | (0.0435) | (0.0196) | (0.0181) | (0.0228) |
| Constant | -24.0893*** | -23.7474*** | -20.8057*** | -16.8086*** | -13.7888*** | -7.7852*** | 3.2974 | 2.3969 | 5.1255 | 1.8976* | 5.3944*** | 7.7234*** |
| | (3.9920) | (4.1507) | (4.8468) | (1.5228) | (1.5791) | (1.7579) | (2.3290) | (2.2959) | (3.3782) | (1.1215) | (1.0721) | (1.2948) |
| Other climate variables+ | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Soils and control variables+ | NO | YES | YES | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Farm types (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| States (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| Observations | 17,351 | 17,351 | 17,351 | 58,743 | 58,743 | 58,743 | 2,695 | 2,695 | 2,695 | 5,596 | 5,596 | 5,596 |
| R-squared | 0.048 | 0.082 | 0.120 | 0.070 | 0.095 | 0.113 | 0.162 | 0.318 | 0.365 | 0.185 | 0.356 | 0.413 |
| **Mean VIF** | **729.90** | **411.78** | **369.44** | **684.91** | **371.16** | **360.03** | **1008.88** | **635.03** | **638.64** | **866.14** | **511.06** | **513.60** |

+ Output omitted (available upon request)
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 2.18 Ricardian model using quarterly climate (all farms-demeaned)

| | | 2012 | | | 2014 | | | 2012 | | | 2014 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| | | **Climate** | | | **Climate** | | | **Climate** | | | **Climate** | |
| *Temp. spring* | 0.2080* | -0.0041 | -0.1496 | -0.5926*** | -0.6531*** | -0.6299*** | -0.2403*** | -0.2883*** | -0.0262 | -0.1102*** | -0.1209*** | -0.0130 |
| | (0.1223) | (0.1348) | (0.1777) | (0.0667) | (0.0719) | (0.1049) | (0.0565) | (0.0568) | (0.0814) | (0.0377) | (0.0370) | (0.0548) |
| *Temp. spring sq.* | 0.0075 | 0.0177 | -0.0036 | 0.0123** | 0.0197*** | 0.0156** | -0.0070 | 0.0074 | 0.0065 | -0.0219*** | -0.0104*** | -0.0097** |
| | (0.0115) | (0.0120) | (0.0143) | (0.0057) | (0.0059) | (0.0066) | (0.0068) | (0.0062) | (0.0083) | (0.0038) | (0.0034) | (0.0041) |
| *Temp. summer* | -0.6501*** | -1.1023*** | -0.6734*** | 1.0051*** | 1.0987*** | 1.1821*** | 0.0716 | 0.0100 | -0.2001** | -0.1044* | -0.3305*** | -0.3263*** |
| | (0.1927) | (0.1996) | (0.2177) | (0.1185) | (0.1206) | (0.1415) | (0.0787) | (0.0793) | (0.0875) | (0.0616) | (0.0582) | (0.0671) |
| *Temp. summer sq.* | -0.0779*** | -0.0580*** | -0.0673*** | -0.0318*** | -0.0286*** | -0.0198** | -0.0127* | -0.0188*** | -0.0103 | 0.0020 | 0.0145*** | 0.0117*** |
| | (0.0131) | (0.0136) | (0.0159) | (0.0059) | (0.0062) | (0.0077) | (0.0065) | (0.0062) | (0.0083) | (0.0033) | (0.0033) | (0.0043) |
| *Temp. autumn* | 1.0307*** | 1.5624*** | 1.3635*** | -0.4896*** | -0.7096*** | -1.0416*** | 0.0662 | 0.0950 | 0.2349** | 0.1879** | 0.5458*** | 0.5379*** |
| | (0.2704) | (0.2801) | (0.3079) | (0.1632) | (0.1662) | (0.1896) | (0.1052) | (0.1058) | (0.1190) | (0.0835) | (0.0795) | (0.0934) |
| *Temp. autumn sq.* | 0.0867*** | 0.0138 | 0.0448* | 0.0242*** | 0.0217** | 0.0115 | 0.0167** | 0.0112 | 0.0109 | 0.0016 | -0.0274*** | -0.0078 |
| | (0.0172) | (0.0185) | (0.0229) | (0.0089) | (0.0092) | (0.0122) | (0.0074) | (0.0071) | (0.0098) | (0.0044) | (0.0044) | (0.0061) |
| *Temp. winter* | -0.3775** | -0.4740** | -0.6539*** | 0.4058*** | 0.6068*** | 0.7782*** | 0.1456* | 0.1580** | 0.0151 | 0.0379 | -0.1517*** | -0.2064*** |
| | (0.1825) | (0.1944) | (0.2258) | (0.1047) | (0.1083) | (0.1318) | (0.0788) | (0.0796) | (0.0924) | (0.0568) | (0.0558) | (0.0662) |
| *Temp. winter sq.* | -0.0182* | 0.0085 | 0.0076 | -0.0032 | -0.0143** | 0.0026 | -0.0040 | -0.0055 | -0.0095 | 0.0071** | 0.0186*** | 0.0011 |
| | (0.0103) | (0.0109) | (0.0127) | (0.0055) | (0.0057) | (0.0070) | (0.0056) | (0.0051) | (0.0073) | (0.0034) | (0.0033) | (0.0040) |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Rain. spring* | 1.5636*** | 1.7715*** | 0.5111 | 0.0184 | 0.2815** | 0.7473*** | 0.7737*** | 0.7752*** | 1.1298** | -0.0135 | -0.0538 | -0.2695* |
| | (0.3667) | (0.3776) | (0.5219) | (0.1341) | (0.1385) | (0.1993) | (0.2831) | (0.2885) | (0.5259) | (0.1143) | (0.1060) | (0.1596) |
| *Rain. spring sq.* | -0.8231*** | -0.8294*** | -0.6185*** | 0.1634*** | 0.1405*** | 0.0101 | -0.2332 | -0.0037 | -0.3196 | -0.0501 | -0.0108 | 0.0033 |
| | (0.1107) | (0.1151) | (0.1258) | (0.0447) | (0.0454) | (0.0516) | (0.1652) | (0.1747) | (0.2463) | (0.0364) | (0.0299) | (0.0330) |
| *Rain. summer* | 0.5230*** | 0.3170*** | 0.2870** | 0.5461*** | 0.6019*** | 0.3344*** | -0.0881* | -0.0865* | -0.1658*** | -0.1172*** | -0.0716** | -0.1402*** |
| | (0.1002) | (0.1084) | (0.1228) | (0.0505) | (0.0534) | (0.0599) | (0.0513) | (0.0504) | (0.0611) | (0.0303) | (0.0288) | (0.0320) |
| *Rain. summer sq.* | -0.0335*** | -0.0204* | -0.0050 | -0.0128*** | -0.0257*** | -0.0019 | 0.0223** | 0.0230** | 0.0111 | 0.0083** | 0.0080** | 0.0094*** |
| | (0.0111) | (0.0117) | (0.0127) | (0.0046) | (0.0048) | (0.0051) | (0.0098) | (0.0100) | (0.0111) | (0.0035) | (0.0034) | (0.0034) |
| *Rain. autumn* | -0.4473** | -0.3141 | -0.2261 | -0.5412*** | -0.6062*** | -0.2050* | 0.0510 | -0.0375 | -0.1131 | -0.0438 | 0.0482 | 0.1285* |
| | (0.2014) | (0.2083) | (0.2334) | (0.0923) | (0.0951) | (0.1075) | (0.1174) | (0.1113) | (0.1295) | (0.0680) | (0.0623) | (0.0692) |
| *Rain. autumn sq.* | 0.1307*** | 0.1014*** | 0.0847*** | -0.0425*** | -0.0309** | -0.0509*** | -0.0836** | -0.0548* | 0.0412 | -0.0084 | -0.0236*** | -0.0180* |
| | (0.0260) | (0.0265) | (0.0284) | (0.0140) | (0.0142) | (0.0155) | (0.0324) | (0.0325) | (0.0395) | (0.0091) | (0.0090) | (0.0094) |
| *Rain. winter* | -1.5054*** | -0.6984* | 0.3292 | 0.3839** | 0.6697*** | -0.0046 | -1.1871*** | -0.6996*** | -0.5787* | -0.0575 | -0.0678 | 0.0411 |
| | (0.3550) | (0.3589) | (0.4004) | (0.1690) | (0.1754) | (0.2001) | (0.2574) | (0.2474) | (0.3115) | (0.1461) | (0.1300) | (0.1568) |
| *Rain. winter sq.* | -0.0248 | -0.1344** | -0.2211*** | 0.1140*** | 0.0513 | 0.1614*** | 0.6948*** | 0.3451** | 0.1630 | 0.0820** | 0.0570* | 0.0760*** |
| | (0.0588) | (0.0601) | (0.0651) | (0.0366) | (0.0382) | (0.0426) | (0.1781) | (0.1711) | (0.2112) | (0.0401) | (0.0326) | (0.0293) |
| *Temp. sp*Rain. sp* | 0.0458 | 0.1665*** | 0.2953*** | -0.0176 | -0.0676*** | 0.0080 | 0.0091 | -0.0273 | -0.0213 | 0.0219 | 0.0447*** | 0.0477*** |
| | (0.0529) | (0.0547) | (0.0739) | (0.0218) | (0.0227) | (0.0270) | (0.0355) | (0.0351) | (0.0575) | (0.0143) | (0.0135) | (0.0177) |
| *Temp. su*Rain. su* | -0.1299*** | -0.0648*** | 0.0419* | -0.0192*** | -0.0013 | 0.0161* | -0.0124 | -0.0229** | -0.0343*** | -0.0128*** | -0.0035 | -0.0052 |
| | (0.0200) | (0.0208) | (0.0242) | (0.0071) | (0.0075) | (0.0087) | (0.0112) | (0.0100) | (0.0123) | (0.0047) | (0.0044) | (0.0052) |
| *Temp. au*Rain. au* | 0.0426 | -0.0581 | -0.2068*** | -0.0193 | 0.0095 | -0.0455*** | 0.0131 | -0.0016 | 0.0283 | 0.0060 | -0.0155** | 0.0158* |
| | (0.0341) | (0.0361) | (0.0419) | (0.0121) | (0.0128) | (0.0158) | (0.0202) | (0.0187) | (0.0239) | (0.0081) | (0.0073) | (0.0088) |
| *Temp. wi*Rain. wi* | 0.0364 | 0.0638 | 0.0935* | 0.1292*** | 0.0777*** | 0.0870*** | 0.0179 | 0.0750** | -0.0027 | -0.0075 | 0.0576*** | -0.0456** |
| | (0.0427) | (0.0445) | (0.0525) | (0.0223) | (0.0230) | (0.0291) | (0.0451) | (0.0321) | (0.0435) | (0.0196) | (0.0181) | (0.0228) |
| Constant | 1.8434*** | 2.3802*** | 2.2119*** | -2.5309*** | -2.3317*** | -2.3957*** | 8.3078*** | 8.3145*** | 7.6482*** | 7.9378*** | 7.9390*** | 7.7548*** |
| | (0.1568) | (0.1662) | (0.5013) | (0.0727) | (0.0759) | (0.2632) | (0.0833) | (0.0841) | (0.3068) | (0.0524) | (0.0496) | (0.3235) |
| Other climate variables+ | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Soils and control variables+ | NO | YES | YES | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Farm types (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| States (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| Observations | 17,351 | 17,351 | 17,351 | 58,743 | 58,743 | 58,743 | 2,695 | 2,695 | 2,695 | 5,596 | 5,596 | 5,596 |
| R-squared | 0.048 | 0.082 | 0.120 | 0.070 | 0.095 | 0.113 | 0.162 | 0.318 | 0.365 | 0.185 | 0.356 | 0.413 |
| **Mean VIF** | **44.80** | **25.93** | **23.23** | **55.17** | **30.31** | **28.22** | **51.83** | **32.88** | **33.95** | **60.38** | **35.70** | **35.10** |

+ Output omitted (available upon request)
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 2.19 Ricardian model using six-monthly climate (all farms-non demeaned)

| | 2012 | | | 2014 | | | 2012 | | | 2014 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| | | **Climate** | | | **Climate** | | | **Climate** | | | **Climate** | |
| *Temp. spsu* | 1.8217*** | 1.4956*** | 1.9804*** | 3.5134*** | 2.1280*** | 1.2032*** | 0.6250*** | 0.1013 | -0.3621 | 0.6695*** | 0.4888*** | -0.3066* |
| | (0.3611) | (0.3889) | (0.5774) | (0.1681) | (0.1761) | (0.2739) | (0.1889) | (0.2011) | (0.3789) | (0.0925) | (0.0932) | (0.1744) |
| *Temp. spsu sq.* | -0.0340*** | -0.0372*** | -0.0503*** | -0.0573*** | -0.0351*** | -0.0191*** | -0.0138*** | -0.0042 | 0.0044 | -0.0155*** | -0.0122*** | 0.0045 |
| | (0.0077) | (0.0083) | (0.0122) | (0.0035) | (0.0036) | (0.0056) | (0.0039) | (0.0043) | (0.0080) | (0.0019) | (0.0019) | (0.0036) |
| *Temp. auwi* | -0.9862*** | -0.5818** | -0.9550** | -2.5708*** | -1.4781*** | -1.2792*** | -0.1582 | 0.0136 | 0.4275** | 0.0407 | -0.0151 | 0.4733*** |
| | (0.2132) | (0.2356) | (0.3936) | (0.1236) | (0.1314) | (0.2286) | (0.1063) | (0.1128) | (0.2159) | (0.0596) | (0.0658) | (0.1325) |
| *Temp. auwi sq.* | 0.0325*** | 0.0266*** | 0.0343*** | 0.0602*** | 0.0360*** | 0.0316*** | 0.0078** | 0.0038 | -0.0055 | 0.0030* | 0.0039** | -0.0099*** |
| | (0.0058) | (0.0063) | (0.0099) | (0.0032) | (0.0033) | (0.0053) | (0.0031) | (0.0034) | (0.0056) | (0.0016) | (0.0017) | (0.0031) |
| *Rain. spsu* | 1.6162*** | 0.2900 | -1.1470** | 1.3510*** | 0.7741*** | 0.3385* | 0.0717 | -0.1640 | 0.0564 | 0.4945*** | 0.3650*** | 0.1326 |
| | (0.3288) | (0.3760) | (0.4868) | (0.1357) | (0.1428) | (0.1792) | (0.1814) | (0.1782) | (0.2225) | (0.0882) | (0.0925) | (0.1009) |
| *Rain. spsu sq.* | -0.0157*** | -0.0142*** | -0.0110* | -0.0058*** | -0.0164*** | -0.0207*** | 0.0189*** | 0.0255*** | 0.0197*** | 0.0078*** | 0.0070*** | 0.0054*** |
| | (0.0046) | (0.0049) | (0.0061) | (0.0020) | (0.0021) | (0.0025) | (0.0041) | (0.0040) | (0.0052) | (0.0013) | (0.0015) | (0.0017) |
| *Rain. auwi* | -0.3243 | 0.7848** | 2.3754*** | -0.3774*** | -0.1192 | 0.1979 | 0.3114 | 0.5014 | -0.0208 | -0.4129*** | -0.2802*** | -0.3097*** |
| | (0.3672) | (0.3947) | (0.4809) | (0.1386) | (0.1427) | (0.1735) | (0.3249) | (0.3502) | (0.3746) | (0.0862) | (0.0910) | (0.1044) |
| *Rain. auwi sq.* | 0.0185*** | -0.0012 | -0.0008 | 0.0145*** | 0.0149*** | 0.0157*** | -0.0118 | -0.0103 | 0.0121 | -0.0011 | -0.0036 | -0.0053** |
| | (0.0053) | (0.0056) | (0.0060) | (0.0036) | (0.0038) | (0.0040) | (0.0091) | (0.0085) | (0.0137) | (0.0022) | (0.0027) | (0.0024) |
| *Temp. spsu*Rain. spsu* | -0.0425*** | 0.0064 | 0.0578*** | -0.0525*** | -0.0180*** | 0.0116* | -0.0161** | -0.0089 | -0.0135 | -0.0318*** | -0.0244*** | -0.0136*** |
| | (0.0129) | (0.0144) | (0.0180) | (0.0052) | (0.0056) | (0.0067) | (0.0067) | (0.0068) | (0.0084) | (0.0034) | (0.0036) | (0.0039) |
| *Temp. auwi*Rain. auwi* | -0.0067 | -0.0361** | -0.1051*** | 0.0080 | -0.0035 | -0.0225*** | -0.0097 | -0.0173 | -0.0058 | 0.0209*** | 0.0171*** | 0.0220*** |
| | (0.0156) | (0.0170) | (0.0211) | (0.0063) | (0.0067) | (0.0083) | (0.0155) | (0.0171) | (0.0192) | (0.0039) | (0.0041) | (0.0049) |
| Constant | -16.8012*** | -12.9038*** | -13.0267*** | -26.3734*** | -18.6192*** | -8.9897*** | 1.9562 | 6.5957*** | 7.6567*** | -0.1589 | 2.0571*** | 6.8663*** |
| | (3.0916) | (3.2268) | (4.1312) | (1.2250) | (1.2796) | (1.6030) | (1.6223) | (1.7761) | (2.9128) | (0.7451) | (0.7195) | (1.1090) |
| Other climate variables+ | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Soils and control variables+ | NO | YES | YES | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Farm types (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| States (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| Observations | 17,351 | 17,351 | 17,351 | 58,743 | 58,743 | 58,743 | 2,695 | 2,695 | 2,695 | 5,596 | 5,596 | 5,596 |
| R-squared | 0.039 | 0.073 | 0.114 | 0.053 | 0.083 | 0.111 | 0.132 | 0.300 | 0.360 | 0.169 | 0.329 | 0.405 |
| **Mean VIF** | **203.13** | **82.11** | **97.90** | **160.25** | **61.95** | **83.19** | **208.26** | **93.41** | **158.04** | **167.31** | **69.09** | **123.67** |

+ Output omitted (available upon request)
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 2.20 Ricardian model using six-monthly climate (all farms-demeaned)

| | | 2012 | | | 2014 | | | 2012 | | | 2014 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| - | | **Climate** | | | **Climate** | | | **Climate** | | | **Climate** | |
| *Temp. spsu* | 0.0128 | -0.2336*** | -0.1218 | 0.6151*** | 0.4339*** | 0.4073*** | -0.0971*** | -0.1320*** | -0.1932*** | -0.1899*** | -0.1827*** | -0.1566*** |
| | (0.0534) | (0.0611) | (0.0980) | (0.0291) | (0.0318) | (0.0549) | (0.0280) | (0.0276) | (0.0450) | (0.0175) | (0.0172) | (0.0281) |
| *Temp. spsu sq.* | -0.0340*** | -0.0372*** | -0.0503*** | -0.0573*** | -0.0351*** | -0.0191*** | -0.0138*** | -0.0042 | 0.0044 | -0.0155*** | -0.0122*** | 0.0045 |
| | (0.0077) | (0.0083) | (0.0122) | (0.0035) | (0.0036) | (0.0056) | (0.0039) | (0.0043) | (0.0080) | (0.0019) | (0.0019) | (0.0036) |
| *Temp. auwi* | 0.2348*** | 0.3167*** | 0.0089 | -0.2785*** | -0.1377*** | -0.1733*** | 0.1287*** | 0.1271*** | 0.1987*** | 0.2052*** | 0.1773*** | 0.1491*** |
| | (0.0458) | (0.0533) | (0.0965) | (0.0279) | (0.0303) | (0.0598) | (0.0221) | (0.0217) | (0.0468) | (0.0144) | (0.0144) | (0.0312) |
| *Temp. auwi sq.* | 0.0325*** | 0.0266*** | 0.0343*** | 0.0602*** | 0.0360*** | 0.0316*** | 0.0078** | 0.0038 | -0.0055 | 0.0030* | 0.0039** | -0.0099*** |
| | (0.0058) | (0.0063) | (0.0099) | (0.0032) | (0.0033) | (0.0053) | (0.0031) | (0.0034) | (0.0056) | (0.0016) | (0.0017) | (0.0031) |
| *Rain. spsu* | 0.4636*** | 0.3071*** | 0.1140 | 0.0947*** | 0.1781*** | 0.3631*** | -0.1896*** | -0.2056*** | -0.1364*** | -0.1801*** | -0.1441*** | -0.1401*** |
| | (0.0638) | (0.0742) | (0.0978) | (0.0332) | (0.0372) | (0.0473) | (0.0317) | (0.0308) | (0.0483) | (0.0178) | (0.0180) | (0.0245) |
| *Rain. spsu sq.* | -0.0157*** | -0.0142*** | -0.0110* | -0.0058*** | -0.0164*** | -0.0207*** | 0.0189*** | 0.0255*** | 0.0197*** | 0.0078*** | 0.0070*** | 0.0054*** |
| | (0.0046) | (0.0049) | (0.0061) | (0.0020) | (0.0021) | (0.0025) | (0.0041) | (0.0040) | (0.0052) | (0.0013) | (0.0015) | (0.0017) |
| *Rain. auwi* | -0.3292*** | 0.0870 | 0.3594*** | -0.1190** | -0.0744 | -0.1096* | 0.0686 | 0.1154* | -0.0836 | -0.0209 | 0.0276 | 0.0821** |
| | (0.1084) | (0.1137) | (0.1288) | (0.0503) | (0.0532) | (0.0606) | (0.0688) | (0.0659) | (0.0839) | (0.0337) | (0.0334) | (0.0353) |
| *Rain. auwi sq.* | 0.0185*** | -0.0012 | -0.0008 | 0.0145*** | 0.0149*** | 0.0157*** | -0.0118 | -0.0103 | 0.0121 | -0.0011 | -0.0036 | -0.0053** |
| | (0.0053) | (0.0056) | (0.0060) | (0.0036) | (0.0038) | (0.0040) | (0.0091) | (0.0085) | (0.0137) | (0.0022) | (0.0027) | (0.0024) |
| *Temp. spsu*Rain. spsu* | -0.0425*** | 0.0064 | 0.0578*** | -0.0525*** | -0.0180*** | 0.0116* | -0.0161** | -0.0089 | -0.0135 | -0.0318*** | -0.0244*** | -0.0136*** |
| | (0.0129) | (0.0144) | (0.0180) | (0.0052) | (0.0056) | (0.0067) | (0.0067) | (0.0068) | (0.0084) | (0.0034) | (0.0036) | (0.0039) |
| *Temp. auwi*Rain. auwi* | -0.0067 | -0.0361** | -0.1051*** | 0.0080 | -0.0035 | -0.0225*** | -0.0097 | -0.0173 | -0.0058 | 0.0209*** | 0.0171*** | 0.0220*** |
| | (0.0156) | (0.0170) | (0.0211) | (0.0063) | (0.0067) | (0.0083) | (0.0155) | (0.0171) | (0.0192) | (0.0039) | (0.0041) | (0.0049) |
| Constant | 2.1007*** | 2.4736*** | 1.8332*** | -2.8741*** | -2.6579*** | -2.7580*** | 8.2549*** | 8.1813*** | 7.5206*** | 7.9792*** | 7.9428*** | 7.7331*** |
| | (0.1266) | (0.1348) | (0.4481) | (0.0620) | (0.0642) | (0.2416) | (0.0408) | (0.0465) | (0.2440) | (0.0269) | (0.0281) | (0.3036) |
| Other climate variables+ | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Soils and control variables+ | NO | YES | YES | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Farm types (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| States (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| Observations | 17,351 | 17,351 | 17,351 | 58,743 | 58,743 | 58,743 | 2,695 | 2,695 | 2,695 | 5,596 | 5,596 | 5,596 |
| R-squared | 0.039 | 0.073 | 0.114 | 0.053 | 0.083 | 0.111 | 0.132 | 0.300 | 0.360 | 0.169 | 0.329 | 0.405 |
| **Mean VIF** | **8.47** | **4.35** | **5.50** | **7.56** | **3.88** | **5.60** | **8.51** | **4.46** | **8.55** | **8.17** | **4.10** | **7.31** |

+ Output omitted (available upon request)
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 2.21 Ricardian model using annual climate (all farms-non demeaned)

| | 2012 | | | 2014 | | | 2012 | | | 2014 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| | | **Climate** | | | **Climate** | | | **Climate** | | | **Climate** | |
| *Temperature* | -0.1205 | -0.0139 | -0.0177 | 0.3102*** | 0.2345*** | -0.1498 | 0.0742 | -0.0873 | -0.0768 | 0.3246*** | 0.1608*** | 0.1307** |
| | (0.1854) | (0.1974) | (0.2312) | (0.0787) | (0.0856) | (0.1002) | (0.0685) | (0.0760) | (0.1021) | (0.0411) | (0.0434) | (0.0551) |
| *Temperature square* | 0.0121** | 0.0052 | 0.0011 | 0.0028 | 0.0018 | 0.0103*** | 0.0011 | 0.0049*** | 0.0026 | -0.0049*** | -0.0019* | -0.0040*** |
| | (0.0047) | (0.0051) | (0.0058) | (0.0020) | (0.0022) | (0.0025) | (0.0016) | (0.0018) | (0.0023) | (0.0010) | (0.0011) | (0.0013) |
| *Rainfall* | 0.6231*** | 0.5696*** | 0.4104** | -0.1647*** | 0.0449 | 0.2160*** | 0.1067* | 0.2199*** | 0.0739 | 0.1313*** | 0.1107*** | -0.0651* |
| | (0.1137) | (0.1351) | (0.1611) | (0.0418) | (0.0481) | (0.0540) | (0.0583) | (0.0742) | (0.1212) | (0.0245) | (0.0288) | (0.0373) |
| *Rainfall square* | -0.0030*** | -0.0086*** | -0.0072*** | 0.0046*** | -0.0015** | -0.0040*** | 0.0022* | 0.0051*** | 0.0053** | 0.0012*** | 0.0008** | 0.0007 |
| | (0.0011) | (0.0013) | (0.0016) | (0.0005) | (0.0006) | (0.0007) | (0.0012) | (0.0013) | (0.0021) | (0.0003) | (0.0003) | (0.0005) |
| *Temperature*Rainfall* | -0.0190*** | -0.0068 | -0.0033 | -0.0022 | 0.0007 | 0.0003 | -0.0087*** | -0.0145*** | -0.0083 | -0.0096*** | -0.0071*** | 0.0013 |
| | (0.0050) | (0.0057) | (0.0068) | (0.0019) | (0.0021) | (0.0024) | (0.0027) | (0.0034) | (0.0052) | (0.0010) | (0.0012) | (0.0015) |
| Constant | -2.7140 | -2.6620 | -0.5479 | -9.5672*** | -8.4596*** | -4.8058*** | 6.4317*** | 7.4676*** | 7.3918*** | 3.7684*** | 4.9697*** | 6.1047*** |
| | (1.8735) | (1.9817) | (2.3716) | (0.8123) | (0.8966) | (1.0713) | (0.7839) | (0.8606) | (1.2400) | (0.4349) | (0.4652) | (0.6801) |
| Other climate variables+ | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Soils and control variables+ | NO | YES | YES | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Farm types (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| States (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| Observations | 17,351 | 17,351 | 17,351 | 58,743 | 58,743 | 58,743 | 2,695 | 2,695 | 2,695 | 5,596 | 5,596 | 5,596 |
| R-squared | 0.035 | 0.071 | 0.112 | 0.041 | 0.079 | 0.109 | 0.091 | 0.277 | 0.349 | 0.112 | 0.296 | 0.395 |
| **Mean VIF** | **84.49** | **23.06** | **18.59** | **52.6** | **14.37** | **11.61** | **65.59** | **20.93** | **23.15** | **52.52** | **15.33** | **16.14** |

+ Output omitted (available upon request)
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 2.22 Ricardian model using annual climate (all farms-demeaned)

| | 2012 | | | 2014 | | | 2012 | | | 2014 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **NetRev/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** | **Rent/ha** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (1) | (2) | (3) | (4) | (5) | (6) |
| | | **Climate** | | | **Climate** | | | **Climate** | | | **Climate** | |
| *Temperature* | 0.2423*** | 0.1521*** | 0.0047 | 0.4070*** | 0.3148*** | 0.2807*** | 0.0744*** | 0.0475*** | -0.0094 | 0.0507*** | 0.0321*** | -0.0286*** |
| | (0.0203) | (0.0240) | (0.0341) | (0.0089) | (0.0111) | (0.0151) | (0.0078) | (0.0084) | (0.0159) | (0.0048) | (0.0052) | (0.0089) |
| *Temperature square* | 0.0121** | 0.0052 | 0.0011 | 0.0028 | 0.0018 | 0.0103*** | 0.0011 | 0.0049*** | 0.0026 | -0.0049*** | -0.0019* | -0.0040*** |
| | (0.0047) | (0.0051) | (0.0058) | (0.0020) | (0.0022) | (0.0025) | (0.0016) | (0.0018) | (0.0023) | (0.0010) | (0.0011) | (0.0013) |
| *Rainfall* | 0.1686*** | 0.2839*** | 0.2238*** | -0.1222*** | 0.0305** | 0.1463*** | -0.0591*** | -0.0419*** | -0.0493** | -0.0558*** | -0.0289*** | -0.0285** |
| | (0.0211) | (0.0300) | (0.0395) | (0.0097) | (0.0131) | (0.0164) | (0.0082) | (0.0116) | (0.0223) | (0.0049) | (0.0066) | (0.0114) |
| *Rainfall square* | -0.0030*** | -0.0086*** | -0.0072*** | 0.0046*** | -0.0015** | -0.0040*** | 0.0022* | 0.0051*** | 0.0053** | 0.0012*** | 0.0008** | 0.0007 |
| | (0.0011) | (0.0013) | (0.0016) | (0.0005) | (0.0006) | (0.0007) | (0.0012) | (0.0013) | (0.0021) | (0.0003) | (0.0003) | (0.0005) |
| *Temperature*Rainfall* | -0.0190*** | -0.0068 | -0.0033 | -0.0022 | 0.0007 | 0.0003 | -0.0087*** | -0.0145*** | -0.0083 | -0.0096*** | -0.0071*** | 0.0013 |
| | (0.0050) | (0.0057) | (0.0068) | (0.0019) | (0.0021) | (0.0024) | (0.0027) | (0.0034) | (0.0052) | (0.0010) | (0.0012) | (0.0015) |
| Constant | 2.2379*** | 2.4123*** | 1.7307*** | -2.8993*** | -2.6657*** | -2.3048*** | 8.2725*** | 8.1772*** | 7.2790*** | 8.0278*** | 7.9820*** | 7.5525*** |
| | (0.1049) | (0.1091) | (0.4430) | (0.0590) | (0.0605) | (0.2334) | (0.0336) | (0.0368) | (0.2439) | (0.0253) | (0.0249) | (0.3024) |
| Other climate variables+ | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Soils and control variables+ | NO | YES | YES | NO | YES | YES | NO | YES | YES | NO | YES | YES |
| Farm types (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| States (FE)+ | NO | NO | YES | NO | NO | YES | NO | NO | YES | NO | NO | YES |
| Observations | 17,351 | 17,351 | 17,351 | 58,743 | 58,743 | 58,743 | 2,695 | 2,695 | 2,695 | 5,596 | 5,596 | 5,596 |
| R-squared | 0.035 | 0.071 | 0.112 | 0.041 | 0.079 | 0.109 | 0.091 | 0.277 | 0.349 | 0.112 | 0.296 | 0.395 |
| **Mean VIF** | **2.24** | **1.84** | **2.53** | **1.69** | **1.63** | **2.42** | **1.71** | **1.73** | **4.05** | **1.59** | **1.60** | **3.57** |

+ Output omitted (available upon request)
Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Table 2.23 Parsimonious Ricardian model using six-monthly climate (all farms)

| | NetRev/ha | | Rent/ha | |
|---|---|---|---|---|
| VARIABLES | 2012 | 2014 | 2012 | 2014 |
| | (1) | (2) | (3) | (4) |
| | **Climate** | | | |
| *Temp. spsu* | -0.1218 | 0.4073*** | -0.1932*** | -0.1566*** |
| | (0.0980) | (0.0549) | (0.0450) | (0.0281) |
| *Temp. spsu sq.* | -0.0503*** | -0.0191*** | 0.0044 | 0.0045 |
| | (0.0122) | (0.0056) | (0.0080) | (0.0036) |
| *Temp. auwi* | 0.0089 | -0.1733*** | 0.1987*** | 0.1491*** |
| | (0.0965) | (0.0598) | (0.0468) | (0.0312) |
| *Temp. auwi sq.* | 0.0343*** | 0.0316*** | -0.0055 | -0.0099*** |
| | (0.0099) | (0.0053) | (0.0056) | (0.0031) |
| *Rainfall spsu* | 0.1140 | 0.3631*** | -0.1364*** | -0.1401*** |
| | (0.0978) | (0.0473) | (0.0483) | (0.0245) |
| *Rainfall spsu sq.* | -0.0110* | -0.0207*** | 0.0197*** | 0.0054*** |
| | (0.0061) | (0.0025) | (0.0052) | (0.0017) |
| *Rainfall auwi* | 0.3594*** | -0.1096* | -0.0836 | 0.0821** |
| | (0.1288) | (0.0606) | (0.0839) | (0.0353) |
| *Rainfall auwi sq.* | -0.0008 | 0.0157*** | 0.0121 | -0.0053** |
| | (0.0060) | (0.0040) | (0.0137) | (0.0024) |
| *Temp.*Rain. spsu* | 0.0578*** | 0.0116* | -0.0135 | -0.0136*** |
| | (0.0180) | (0.0067) | (0.0084) | (0.0039) |
| *Temp.*Rain. aiwi* | -0.1051*** | -0.0225*** | -0.0058 | 0.0220*** |
| | (0.0211) | (0.0083) | (0.0192) | (0.0049) |
| | **Other climate variables** | | | |
| *Storms Sp-Su* | 0.0076 | -0.0138* | 0.0221*** | 0.0006 |
| | (0.0157) | (0.0083) | (0.0074) | (0.0043) |
| *Storms Au-Wi* | -0.0034 | 0.0468*** | -0.0224 | 0.0063 |
| | (0.0239) | (0.0144) | (0.0151) | (0.0070) |
| *Clouds Sp-Su* | -0.0123 | -0.0006 | 0.0033 | 0.0016 |
| | (0.0079) | (0.0041) | (0.0039) | (0.0022) |
| *Clouds Au-Wi* | 0.0155* | -0.0019 | -0.0073 | -0.0004 |
| | (0.0087) | (0.0048) | (0.0052) | (0.0028) |
| | **Soils** | | | |
| *Acrisol* | 0.0081 | 0.0095*** | 0.0043 | -0.0037** |
| | (0.0060) | (0.0028) | (0.0030) | (0.0016) |
| *Andosol* | 0.0078 | 0.0078*** | -0.0033 | 0.0018 |
| | (0.0094) | (0.0028) | (0.0063) | (0.0019) |
| *Arenosol* | -0.0036 | -0.0212 | - | 0.0181*** |
| | (0.0327) | (0.0176) | | (0.0047) |
| *Cambisol* | 0.0012 | -0.0013 | 0.0013 | 0.0005 |
| | (0.0034) | (0.0018) | (0.0010) | (0.0008) |
| *Castanozem* | -0.0158*** | -0.0125*** | 0.0008 | 0.0052*** |
| | (0.0049) | (0.0027) | (0.0026) | (0.0014) |
| *Chernozem* | 0.0133 | -0.0606*** | -0.0249*** | 0.0024 |
| | (0.0341) | (0.0170) | (0.0020) | (0.0067) |
| *Feozem* | -0.0193*** | -0.0002 | -0.0020** | -0.0008 |
| | (0.0028) | (0.0014) | (0.0009) | (0.0006) |
| *Fluvisol* | -0.0365** | -0.0232*** | 0.0033* | 0.0006 |
| | (0.0158) | (0.0073) | (0.0019) | (0.0026) |
| Farm types (FE) | YES | YES | YES | YES |
| States (FE) | YES | YES | YES | YES |
| Observations | 17,351 | 58,743 | 2,695 | 5,596 |
| R-squared | 0.114 | 0.111 | 0.360 | 0.405 |

| | NetRev/ha | | Rent/ha | |
|---|---|---|---|---|
| VARIABLES | 2012 | 2014 | 2012 | 2014 |
| | (1) | (2) | (3) | (4) |
| | **Soils** | | | |
| *Gleysol* | -0.0049 | 0.0028 | -0.0066 | -0.0089* |
| | (0.0049) | (0.0039) | (0.0065) | (0.0047) |
| *Litosol* | -0.0057 | -0.0082*** | 0.0015 | 0.0000 |
| | (0.0037) | (0.0020) | (0.0026) | (0.0013) |
| *Luvisol* | -0.0023 | 0.0023 | -0.0016 | -0.0002 |
| | (0.0044) | (0.0021) | (0.0017) | (0.0012) |
| *Nitosol* | 0.0169 | -0.0090 | - | -0.0007 |
| | (0.0126) | (0.0067) | | (0.0063) |
| *Planosol* | 0.0029 | -0.0030 | -0.0014 | -0.0017* |
| | (0.0048) | (0.0028) | (0.0014) | (0.0010) |
| *Ranker* | 0.1560** | 0.1701 | -0.3783 | -0.0546 |
| | (0.0735) | (0.1565) | (0.2565) | (0.1905) |
| *Regosol* | -0.0083*** | -0.0087*** | -0.0003 | -0.0006 |
| | (0.0029) | (0.0016) | (0.0010) | (0.0006) |
| *Rendzina* | 0.0058* | 0.0053** | -0.0014 | -0.0036*** |
| | (0.0034) | (0.0022) | (0.0030) | (0.0014) |
| *Solonchak* | -0.0070 | 0.0031 | -0.0015 | -0.0003 |
| | (0.0058) | (0.0042) | (0.0013) | (0.0012) |
| *Solonetz* | 0.0100 | 0.0362 | -0.0636 | 0.0171 |
| | (0.0448) | (0.0354) | (0.0402) | (0.0110) |
| *Xerosol* | 0.0022 | -0.0009 | 0.0003 | 0.0017*** |
| | (0.0029) | (0.0018) | (0.0008) | (0.0006) |
| *Yermosol* | -0.0133** | -0.0092* | -0.0088*** | -0.0023 |
| | (0.0065) | (0.0047) | (0.0023) | (0.0016) |
| | **Control variables** | | | |
| *Area*1,000* | 0.4093*** | 0.5797*** | -1.4433*** | -0.8609*** |
| | (0.0435) | (0.0521) | (0.1863) | (0.1539) |
| *Area*1,000 sq.* | -0.0055*** | -0.0059*** | 0.3132*** | 0.1130*** |
| | (0.0012) | (0.0013) | (0.0681) | (0.0319) |
| *City* | -0.0103* | 0.0148*** | 0.0022 | -0.0059*** |
| | (0.0055) | (0.0038) | (0.0035) | (0.0023) |
| *Water body* | -0.0045 | -0.0049*** | -0.0040*** | -0.0007 |
| | (0.0031) | (0.0017) | (0.0015) | (0.0010) |
| *River* | -0.0142*** | -0.0011 | -0.0012 | -0.0042*** |
| | (0.0030) | (0.0018) | (0.0015) | (0.0010) |
| *Road density* | -0.0004 | -0.0013*** | 0.0003** | 0.0004*** |
| | (0.0005) | (0.0002) | (0.0001) | (0.0001) |
| *Irrigation* | 0.0192*** | 0.0216*** | 0.0096*** | 0.0089*** |
| | (0.0019) | (0.0010) | (0.0008) | (0.0004) |
| *Ejidal* | -0.0060*** | -0.0128*** | 0.0007* | 0.0005 |
| | (0.0015) | (0.0007) | (0.0004) | (0.0003) |
| *Electricity* | -0.0548 | 0.7018*** | 0.1945*** | 0.2682*** |
| | (0.1376) | (0.0983) | (0.0426) | (0.0340) |
| Constant | 1.8332*** | -2.7580*** | 7.5206*** | 7.7331*** |
| | (0.4481) | (0.2416) | (0.2440) | (0.3036) |
| Farm types (FE) | YES | YES | YES | YES |
| States (FE) | YES | YES | YES | YES |
| Observations | 17,351 | 58,743 | 2,695 | 5,596 |
| R-squared | 0.114 | 0.111 | 0.360 | 0.405 |

+ Null hypothesis: not difference between individual coefficients
++ Null hypothesis: not difference between group of coefficients
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Table 2.24 Climate change scenarios (average losses/gains-all farms, 2012)

| | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
|---|---|---|---|---|---|---|---|---|---|
| | | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* |
| | | | | | 2012 | | | | |
| | **Percentage** | **-25.35** | **2.02** | **-36.84** | **4.69** | **-28.91** | **2.22** | **-53.46** | **7.03** |
| | **Range** | **[-97.98--8.06]** | **[-1.84-29.95]** | **[-118.17--14.16]** | **[-0.05-37.76]** | **[-99.69--7.69]** | **[-5.53-29.91]** | **[-162.45--27.37]** | **[0.19-62.78]** |
| | $ (pesos)/ha | -2,837 | 104 | -4,159 | 277 | -3,266 | 129 | -6,089 | 419 |
| | Range | [-95683-0] | [-443-3770] | [-123515-0] | [-1-6271] | [-104150-0] | [-779-6589] | [-183723-0] | [0-7201] |
| | $ (millions) total | -5,309 | 26 | -7,762 | 80 | -6,041 | 39 | -11,254 | 119 |
| **CCSM4** | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Temp. spsu** | 1.28 [0.99-1.55] | | 1.74 [1.41-2.17] | | 1.55 [1.27-1.96] | | 2.36 [1.82-2.93] | |
| | Temp. auwi** | 1.28 [0.99-1.55] | | 1.74 [1.41-2.17] | | 1.55 [1.27-1.96] | | 2.36 [1.82-2.93] | |
| | Rain. spsu** | -0.07 [-1.18-0.12] | | -0.18 [-1.43-0.03] | | -0.07 [-1.08-0.27] | | -0.26 [-1.87-0.02] | |
| | Rain. auwi** | -0.04 [-1.21-0.10] | | -0.11 [-1.46-0.02] | | -0.04 [-0.03-0.38] | | -0.17 [-2.21-0.01] | |
| | **Percentage** | **-27.89** | **1.55** | **-37.41** | **3.38** | **-33.96** | **6.03** | **-44.52** | **4.20** |
| | **Range** | **[-96.57-22.56]** | **[-10.68-43.84]** | **[-142.02-24.34]** | **[-8.16-45.56]** | **[-93.57-45.24]** | **[-8.09-25.15]** | **[-132.53-36.73]** | **[-18.76-37.9]** |
| | $/ha | -2,958 | 83 | -4,249 | 183 | -3,873 | 382 | -5,059 | 246 |
| | Range | [-58362-5403] | [-844-2668] | [-99668-11222] | [-1565-8825] | [-88639-15185] | [-928-5701] | [-109788-13868] | [-4239-6293] |
| | $ total | -6,103 | 32 | -8,128 | 36 | -7,518 | 126 | -9,844 | 71 |
| **MIROC5** | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Temp. spsu** | 1.60 [1.28-2.16] | | 2.04 [1.58-2.69] | | 1.85 [1.29-2.54] | | 2.48 [1.88-3.16] | |
| | Temp. auwi** | 1.60 [1.28-2.16] | | 2.04 [1.58-2.69] | | 1.85 [1.29-2.54] | | 2.48 [1.88-3.16] | |
| | Rain. spsu** | -0.04 [-1.64-0.54] | | -0.12 [-1.71-0.47] | | -0.23 [-1.02-0.48] | | -0.14 [-1.41-1.00] | |
| | Rain. auwi** | -0.03 [-1.10-0.37] | | -0.05 [-1.02-0.31] | | -0.16 [-0.65-0.26] | | -0.09 [-0.84-0.59] | |
| | **Percentage** | **-20.52** | **2.56** | **-22.93** | **4.68** | **-15.06** | **1.75** | **-38.56** | **9.49** |
| | **Range** | **[-146.7-20.84]** | **[-15.69-26.85]** | **[-125.8-62.6]** | **[-24.92-30.55]** | **[-111.9-58.38]** | **[-26.91-27.71]** | **[-177.36-29.24]** | **[-28.38-51.41]** |
| | $/ha | -2,213 | 122 | -2,580 | 305 | -1,786 | 129 | -4,309 | 651 |
| | Range | [-82858-14941] | [-3257-9805] | [-69498-16647] | [-4587-9054] | [-54573-16676] | [-5360-6384] | [-131611-6833] | [-3202-13672] |
| **MRI-** | $ total | -3,951 | 22 | -4,984 | 101 | -3,308 | 46 | -7,925 | 209 |
| **CGCM3** | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Temp. spsu** | 1.04 [0.82-1.69] | | 1.32 [1.07-1.69] | | 1.27 [0.83-1.69] | | 1.93 [1.26-2.82] | |
| | Temp. auwi** | 1.04 [0.82-1.69] | | 1.32 [1.07-1.69] | | 1.27 [0.83-1.69] | | 1.93 [1.26-2.82] | |
| | Rain. spsu** | -0.09 [-1.11-0.88] | | -0.18 [-1.27-1.43] | | -0.05 [-1.16-1.63] | | -0.36 [-1.96-1.57] | |
| | Rain. auwi** | -0.04 [-1.10-0.51] | | -0.13 [-0.74-1.10] | | -0.04 [-0.25-0.29] | | -0.26 [-1.06-1.07] | |

*Average change in net revenues or rental prices per hectare

**Average change in temperature (degree Celsius) and rainfall (mm.*1,000) with respect to current climate

Minimum and maximum values of the corresponding distributions in brackets

## Table 2.25 Climate change scenarios (average losses/gains-all farms, 2014)

| | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
|---|---|---|---|---|---|---|---|---|---|
| | | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* | NetRev/ha* | Rent/ha* |
| | | | | | 2014 | | | | |
| CCSM4 | **Percentage** | **26.57** | **-0.47** | **34.97** | **-0.70** | **36.84** | **-1.76** | **47.90** | **-1.47** |
| | **Range** | **[-36.61-40.84]** | **[-4.8-18.65]** | **[-38.92-55.42]** | **[-7.84-21.71]** | **[-24.48-51.75]** | **[-6.4-16.67]** | **[-45.53-74.32]** | **[-16.38-26.42]** |
| | $/ha | 4,046 | -38 | 5,315 | -53 | 5,725 | -95 | 7,287 | -99 |
| | Range | [-12539-80591] | [-1366-1399] | [-13951-116421] | [-1487-1901] | [-9510-104639] | [-1616-2107] | [-32688-153438] | [-2045-1965] |
| | $ total | 10,008 | -34 | 13,523 | -51 | 13,013 | -51 | 18,586 | -81 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Temp. spsu** | 1.33 [0.98-1.55] | | 1.78 [1.42-2.17] | | 1.61 [1.27-1.96] | | 2.41 [1.82-2.93] | |
| | Temp. auwi** | 1.33 [0.98-1.55] | | 1.78 [1.42-2.17] | | 1.61 [1.27-1.96] | | 2.41 [1.82-2.93] | |
| | Rain. spsu** | -0.15 [-1.94-0.15] | | -0.25 [-2.28-0.24] | | -0.10 [-1.82-0.34] | | -0.36 [-2.85-0.03] | |
| | Rain. auwi** | -0.08 [-2.15-0.09] | | 0.14 [-2.70-0.15] | | -0.06 [-2.11-0.22] | | -0.21 [-3.95-0.02] | |
| MIROC5 | **Percentage** | **36.22** | **-1.88** | **40.26** | **-0.79** | **37.26** | **-0.77** | **55.60** | **-2.75** |
| | **Range** | **[-33.32-70.94]** | **[-14.46-18.91]** | **[-68.27-85.64]** | **[-16.77-30.64]** | **[-29.2-93.01]** | **[-21.1-18.3]** | **[-35.95-107.29]** | **[-22.52-23.9]** |
| | $/ha | 5,264 | -106 | 5,320 | -58 | 5,187 | -57 | 7,733 | -152 |
| | Range | [-40621-106908] | [-1491-1761] | [-83232-131325] | [-2021-4824] | [-35608-120939] | [-1907-1992] | [-43827-161354] | [-2788-2476] |
| | $ total | 13,390 | -69 | 16,372 | -88 | 13,782 | -61 | 20,887 | -125 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Temp. spsu** | 1.61 [1.22-2.18] | | 2.04 [1.51-2.79] | | 1.83 [1.25-2.65] | | 2.48 [1.84-3.29] | |
| | Temp. auwi** | 1.61 [1.22-2.18] | | 2.04 [1.51-2.79] | | 1.83 [1.25-2.65] | | 2.48 [1.84-3.29] | |
| | Rain. spsu** | -0.09 [-2.33-1.34] | | -0.28 [-3.57-1.50] | | -0.27 [-2.30-2.08] | | -0.24 [-3.08-2.04] | |
| | Rain. auwi** | -0.06 [-1.52-0.69] | | -0.14 [-2.33-0.78] | | -0.17 [-1.50-1.08] | | -0.14 [-2.01-1.19] | |
| MRI-CGCM3 | **Percentage** | **22.64** | **-0.07** | **32.44** | **-1.51** | **37.65** | **-2.88** | **47.49** | **-1.83** |
| | **Range** | **[-36.01-58.05]** | **[-9.18-18.56]** | **[-24.35-86.06]** | **[-17.8-15.06]** | **[-41.27-86.94]** | **[-18.63-14.34]** | **[-29.84-98.33]** | **[-17.99-17.97]** |
| | $/ha | 3,290 | 1 | 5,012 | -62 | 5,837 | -118 | 7,272 | -67 |
| | Range | [-13901-90486] | [-1404-3476] | [-3290-169308] | [-3853-2843] | [-3200-182254] | [-4420-1726] | [-8813-144491] | [-3809-4272] |
| | $ total | 8,229 | -21 | 10,220 | -30 | 11,166 | -43 | 15,335 | -31 |
| | | | | | **Distribution of predicted changes of climate variables** | | | | |
| | Temp. spsu** | 1.08 [ 0.81-2.11] | | 1.32 [0.99-1.89] | | 1.26 [0.83-1.77] | | 1.94 [1.11-3.10] | |
| | Temp. auwi** | 1.08 [ 0.81-2.11] | | 1.32 [0.99-1.89] | | 1.26 [0.83-1.77] | | 1.94 [1.11-3.10] | |
| | Rain. spsu** | -0.13 [-2.94-0.80] | | -0.06 [-2.42-2.12] | | 0.10 [-1.79-2.24] | | -0.21 [-3.44-1.52] | |
| | Rain. auwi** | -0.07 [-2.26-0.48] | | -0.06 [-1.87-1.44] | | 0.04 [-1.38-1.52] | | -0.16 [-2.66-0.77] | |

*Average change in net revenues or rental prices per hectare
**Average change in temperature (degree Celsius) and rainfall (mm.*1,000) with respect to current climate
Minimum and maximum values of the corresponding distributions in brackets

# Chapter 3 The effect of climate change on crop and livestock choices

N.B. To improve the quality of this research, I presented previous versions of this chapter at the following conferences.

- July 2018. 30th International Conference of Agricultural Economists (ICAE). Vancouver, British Columbia, Canada.
- June 2018. 6th World Congress of Environmental and Resource Economists (WCERE). Gothenburg, Sweden.
- August 2017. XV Congress of the European Association of Agricultural Economists (EAAE) Towards Sustainable Agri-Food Systems: Balancing between Markets and Society. Parma, Italy
- June 2017. 23rd Annual Conference of the European Association of Environmental and Resource Economists (EAERE). Athens, Greece.
- February 2017. Global Environmental Challenges Research Workshop. Birmingham, United Kingdom.
- April 2017. Annual Midlands Regional Doctoral Colloquium. Birmingham, United Kingdom.

In some cases, the organisers of such conferences made these versions public as part of the conference proceedings. I received the Dr Ernest Feder award for this research (2nd place). The Economic Research Institute of the National Autonomous University of Mexico (UNAM) gives such award. In some cases, David Maddison and Anindya Banerjee were registered as co-authors of the conference papers. Their contribution to the preparation of the conference papers was minimal. Aside from comments and advice made in the course of supervision there was some editing of the relevant chapter for purposes of reducing its length and rephrasing material for the sake of clarity. I am wholly responsible for the literature review, collection of the data, empirical analysis and interpretation of the results.

## 3.1. Introduction

It is widely agreed that climate change will force farmers to modify their current production decisions. Among other things, such adjustments will have an impact on food supply, prices of agriculture commodities, diets, demand for new lands, etc. The Intergovernmental Panel on Climate Change (IPCC) predicts that average temperature will increase between 0.80ºC and 4.80ºC in 2100 with respect to pre-industrial levels (IPCC, 2014). At the same time, United Nations (UN) expects that the current global population of 7.6 billion would reach 11.2 billion in 2100 (FAO, 2017). These trends may have serious implications for the agricultural sector, especially to food security, land uses, and profitability, if adaptation strategies are not undertaken. Within the set of adaptation strategies, some authors such as Seo and Mendelsohn (2008), Wang et al. (2008), Seo et al. (2010), and Moniruzzaman (2015) treat crop or type of livestock choices as the most basic strategy.

The scarcity of empirical work related to the threat of climate change for crop and livestock choices causes that some relevant questions remain unanswered. We survey those studies that identify the influence of climate on farmers' crop or livestock choices by treating these selections as discrete outcomes. This strand of literature assumes that farmers are already adapted to current climate conditions, in such a case, variation in climate across space is a key factor for identifying how changes on climate would modify agriculturalists' choices in the future. To analyse production decisions, cross-sectional data and the Multinomial Logit (MNL) model are always used in both single and multi-country studies.

Previous studies ignore economic, agronomic and social barriers and assume that farmers can switch from any crop/type of livestock to another without facing such constraints. The use of highly specialised labour, equipment, machinery and facilities imposes economic barriers to the switching process since farmers would need to make large investments in new forms of physical capital to produce a different commodity (Zilberman et al., 2004). Regarding the second type of barriers, it is clear that the physical and chemical characteristics of the soil, existing plagues, pollination, sunlight, availability of water and other agronomic conditions would likely deter some of the switching processes (Free, 1970; Allison, 1973; Perry et al. 2009).

Arguing that climate change adaptation actions, such as crop switching, result from different social process, Jones and Boyd (2011) highlight the importance of taking into account social barriers in empirical analyses. Jones and Boyd identify three types of social barriers to adaptation: i) cognitive behaviour, e.g. risk aversion related to the adaptation action and scepticism about climate change; ii) normative behaviour, e.g. adopting traditional/cultural actions in response to climates changes that would be inappropriate and unwillingness to deviate from traditional practices; and, iii) institutional structure and governance, e.g. restricting access to resources needed to adapt and institutional rigidities.

Given the aforementioned barriers, grouping together (nesting) similar crops or types of livestock could help give any future assessments of the effect of climate change on crops and livestock choices a more realistic viewpoint. To do so, future studies must group together similar alternatives carefully considering economic constraints, agronomic impediments, social barriers and using an econometrically justifiable manner, e.g. nested models.

Taking advantage of a new-plot level data on 31 types of crops and livestock encountered in 219,985 and 168,265 plots, this paper seeks to overcome deficiencies in previous studies and to contribute to the existing literature by: a) relaxing the Independence of Irrelevant Alternatives (IIA) property through the estimation of a Nested Logit (NL) model[101] which accounts for correlation among alternatives; b) analysing likely transitions between arable and pastoral activities; c) using the full set of expected farm gate output prices in the choice

[101] This approach has been applied to different contexts such as the travel-mode choice in Hensher (1986), Greene (2000), Heiss (2002), and Hensher and Greene (2002); the choice of time-of-day for work trips as in McFadden et al. (1977a), Small (1982), Small and Brownstone (1982), and Thobani (1984), and demand for recreational fishing by Hauber and Parsons (2000).

equations; d) employing a plot-level data to account for diversification strategies within a single farm including both pastoral and arable activities; and e) using hundreds of thousands of cases pertaining to a single country from two agricultural years, which makes our dataset several orders of magnitude larger than that used by any existing study.

The main results of this research suggest that assuming IIA distorts predictions of the influence of climate change on crop and livestock choices. It is likely to observe farmers moving away from beverage crops and beef cattle towards fruits because of changes on climatic conditions, not only among types of livestock or among certain crops as other studies conclude. Some factors such as access to markets and information boost the probability to select commodities other than traditional choices while subsidy payments or being part of an indigenous community may have the opposite effect over farmers' decisions.

The structure of the paper is as follows. Section 3.2 presents the literature review. Section 3.3 describes the methods and data used in this analysis. Section 3.4 presents the results of the MNL, the Hausman test for the validity of the IIA property, the results of the NL, dissimilarity parameters that show the correlation among particular alternatives, and some speculations about the impact of climate change on crop and livestock choices. Finally, section 3.5 concludes and provides some insights about future research.

## 3.2. Literature review

### *3.2.1. Multi-country studies*

Dealing first with multi-country studies, Seo and Mendelsohn (2007) explore farmers' choices among 5 'major types' of livestock in 9,000 farms from ten countries in Africa and their main findings suggest that climate indeed influences selections of the type of livestock. Applying also a MNL, Seo et al. (2008b) investigate the probability of farmers selecting any of 5 farm 'types' in 8,500 households within 16 Agro-Ecological Zones (AEZs) in Africa arguing that agriculturalists located in different regions will react differently to changes on climate. In line with this finding, Seo et al. (2008a) group together the full set of alternatives into three 'primary' crops and five 'primary' combinations of crops in 4,882 households in Africa and find differential adaptation strategies among AEZs.

Using data on three 'primary' crops and 6 'primary' combinations of crops in 5,251 African farms, Kurukulasuriya and Mendelsohn (2008) link farmers' choices to net revenues in what they called the 'structural Ricardian model'[102] and argue that those studies that do not account for adaptation strategies, such as crop switching, overestimate harmful effects of climate change on agriculture. Adding further support to the previous argument, Hassan et al. (2008) analyse the same data set grouping the full set of alternatives into eight farm 'types'. Their findings indicate that mono-cropping farms are particularly vulnerable to changes on climate.

In South America, Seo and Mendelsohn (2008) analyse seven 'primary' crop choices in 949 farms from seven countries. Some of their findings coincide with those in African studies however, we observe different results for particular activities such as the dairy cattle sector. These differences are also encountered in Seo et al. (2010) in an investigation that predicts the probability of choosing any of five 'primary' types of livestock in 1,278 South American households. More recently, Reed et al. (2017) provide empirical evidence about the influence of climate on the selection of 10 types of crops in South-East Asia. The improvement of this research over previous studies is the use of plot-level data rather than farm data and the inclusion of the nonlinear interaction effect of temperature and rainfall in the choice equations. Using the same sample, Ou and Mendelsohn (2017) analyse livestock species choices treating the 'primary' animal as the unit of analysis in 525 farms in South-East Asia.

[102] This two-stage method explicitly models farmers' adaptation behaviour. It first models the climate-farmers' choices relationship, e.g. farm-type choices, using the MNL model and then estimates the conditional income for each choice. So, this model captures both the adaptive choices and the effect of climate change on expected income (Mendelsohn and Dinar, 2009).

### 3.2.2. Single-country studies

Turning now to national studies, Wang et al. (2008) use data on nine 'primary' crops grown in 8,405 Chinese farms arguing that the impact of climate change on crop choices in each location will depend on the seasonal distributions of temperature and rainfall and not only on the annual average. Unlike the aforementioned studies, Moniruzzaman (2015) uses pooled cross-sectional data[103] rather than a single cross-section data on three 'primary' rice varieties and other crops[104] from 11,389 farms in Bangladesh. The author discovers that the set of parameters in the choice equations are unstable across time and argues that pooled cross-section data is superior to single cross-section data for simulating the effect of climate change on crop choices.

### 3.2.3. Main findings

The aforementioned studies typically identify the effect of climate on farmers' choices by including linear and square terms of long-term averages of temperature and rainfall from satellite or ground station data in the choice equations. Even though monthly data is typically available, high correlation between monthly values prevent their usage and seasonal or annual figures are preferred. Within the set of explanatory variables, we observe own and cross-prices of a subset of alternatives, soil types, access to electricity or distance to the market as proxies for market access or indicators for commercial farms, farmland area, household size as a proxy for unpaid family labour, water flows, altitude, access to extensions services and credit, farming experience, education, age, gender, age, computer and mobile use, land tenure, share of irrigated areas, crop production, ownership of heavy machinery, and wage rates.

As these studies simulate the effect of climate change on crop or livestock choices assuming different changes on climatic conditions and different baseline climate in the corresponding sampled fields, comparisons may be inappropriate. Instead, we analyse marginal effects

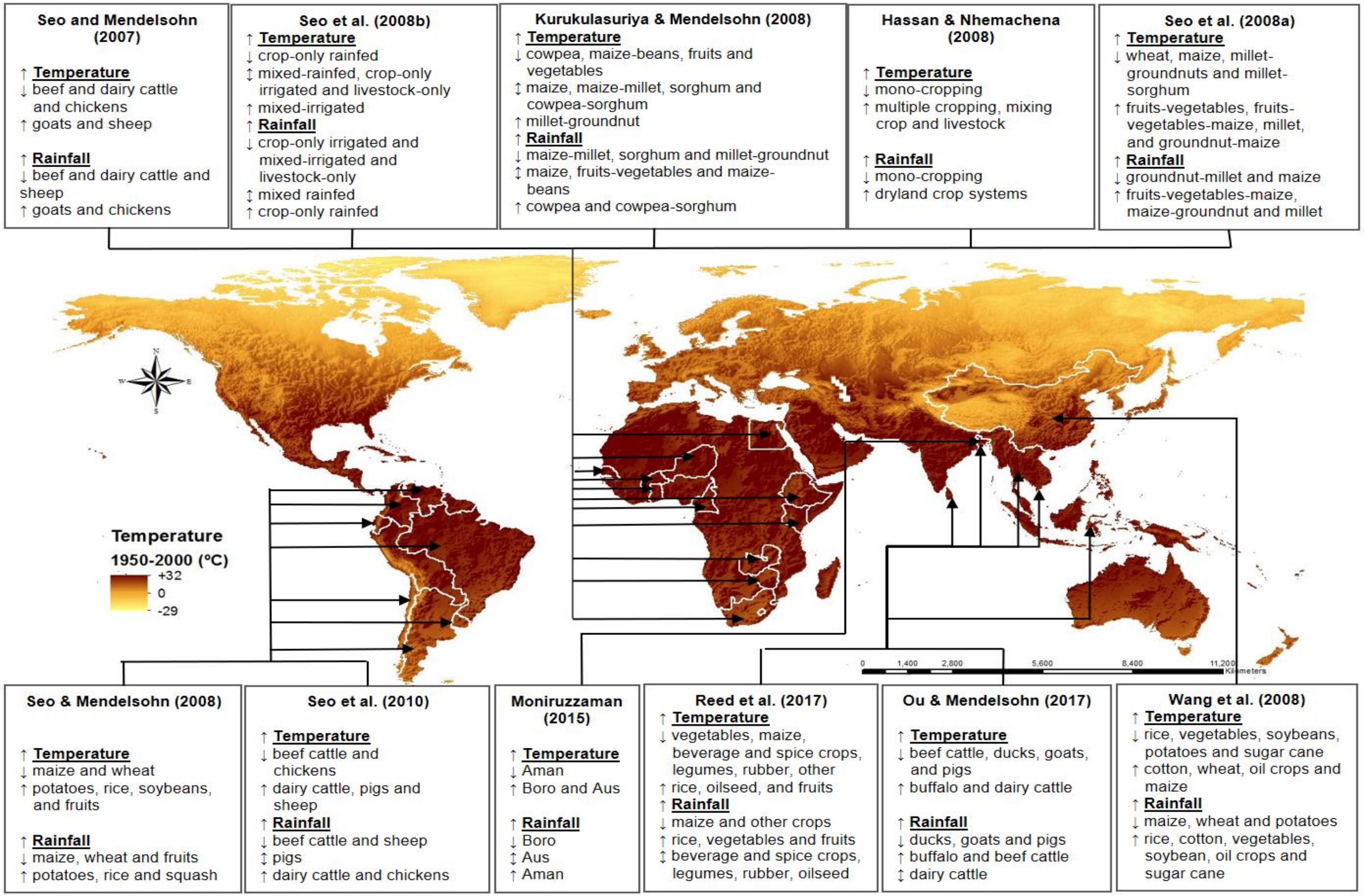
[103] Data on 2000, 2005, and 2010 agricultural years.
[104] This is treated as a single category in the MNL model.

calculated at the sample means where possible. Figure 3.1 shows the main results. Overall, farmers will move away from beef cattle, chickens, ducks, cowpea, vegetables, Aman rice, legumes, rubber, and sugar cane towards sheep, buffalo, millet, Boro rice, Aus rice, oilseeds, and cotton as temperature raises. When these choices are treated as bundles or farm-type selections, farmers will abandon crop-only rainfed, mono-cropping, maize-beans, millet-sorghum, beverage and spice crops practices and adopt fruits-vegetables, fruits-vegetables-maize, groundnut-maize, mixed-irrigated, multiple cropping, mixing crop, and livestock farms.

More rainfall will lead to movements from sheep, ducks, wheat, and sorghum to buffalo, cowpea, millet, squash, vegetables, sugar cane, and cotton commodities. Moreover, from crop-only-irrigated, mixed-irrigated, livestock-only, maize-millet, millet-groundnut, mono cropping, and groundnut-millet towards crop-only-rainfed, cowpea-sorghum, dryland crop systems, fruits-vegetables-maize, and maize-groundnut farm types. For the remaining alternatives, the results are not conclusive.

All the studies assume Independence of Irrelevant Alternatives. This implies that there is proportional substitution between alternatives, that is, the probability of choosing one of the alternatives always rises at the same proportion whenever we remove any of the other alternatives (Train, 2009). For example, under current circumstances a farmer chooses among four alternatives with the following probabilities: $A = \{wheat, 0.40; barley, 0.10; sheep, 0.30; goat, 0.20\}$. However, climate change makes the production of wheat unfeasible. Thus, the assumption of IIA requires that the farmer will choose among the 3 remaining options as follows: $B = \{barley, 0.16\bar{6}; sheep, 0.49\bar{9}; goat, 0.33\bar{3}\}$, that is, the probability of choosing any alternative in $B$ will rise at the same proportion ($66.66\bar{6}\%$) when we remove wheat.

## Figure 3.1 Main findings in previous studies




*Source:* own elaboration based on previous studies. *Africa*: Burkina Fasso, Cameroon, Egypt, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa, Zambia and Zimbabwe. *South America*: Argentina, Brazil, Chile, Colombia, Ecuador, Uruguay and Venezuela. *South-East Asia*: Bangladesh, Indonesia, Sri Lanka, Thailand, and Vietnam. *Country studies*: China and Bangladesh.

Climate change would likely make the production of some commodities unfeasible (or less profitable) and therefore, force farmers to produce other products. Under such circumstances, it is unlikely that we will observe proportional substitution patterns between the remaining and/or new alternatives. Recalling the previous example, a warmer and drier future would increase the probability of choosing goat and sheep more than the probability of choosing barley because these types of livestock tolerate such climate conditions. If this happens then, we will observe something like the following profile: $B = \{barley, 0.10; sheep, 0.54; goat, 0.36\}$. Here, we assume no change in the production of barley and proportional substitution between sheep and goat ($80\%$). Therefore, IIA holds for sheep and goat but not for barley. Furthermore, Figure 3.1 shows that when disaggregated data is available, e.g. individual crops rather than farm-types, previous studies analyse arable and livestock activities in separate analyses. To the best of our knowledge there is no previous work identifying transitions between arable and non-arable activities.

Sometimes not all the studies include a full set of expected output and input prices as there is so little variation in the cross-section that it would in any case be difficult to identify the role played by prices. In all these analyses, crop or livestock choices are modelled using ex-post prices rather than expected output prices. Moreover, because they adopt a discrete choice approach to analyse farm-level data all studies struggle to accommodate the fact that an individual farmer typically diversifies and rotates production. Hence, previous studies typically analyse the ‘primary’ crop type or the ‘dominant’ species of animal. Alternatively, some researchers analyse different types of farms where a ‘type’ of farm refers to a common combination of activities. However, because there are so many possible combinations this can never provide a satisfactory solution.

Reed et al. (2017) is the only investigation that uses plot-level data rather than farm-level data to analyse crop choices. Reed et al model farmers’ current choices among three perennial and seven annual crops grown in South-East Asia using cross-sectional data and the MNL model. Although these authors use plot-level data on observed choices, climate, soils, terrain, and market access, they do not fully account for diversification and rotation practices. Moreover, Reed et al do not include livestock activities in the set of alternatives, which does not allow them to analyse likely transitions from and to non-arable activities.

## 3.3. Methods and materials

### *3.3.1. Theory*

To describe farmers' behaviour let us assume that each farmer: i) maximises profits taking climate and land attributes as exogenous fixed inputs; ii) chooses the alternative that generates the highest expected profit in each plot; iii) is unable to modify input and output prices in the market; and for simplicity, iv) these choices are mutually exclusive. Thus, if a decision maker $i$ selects a crop or type of livestock $j$ in plot $n$ from a set of alternatives, $A = \{1, \ldots, j, \ldots, J\}$, the optimisation problem per farm is defined as follows:

$$\sum_{n=1}^{\bar{n}} \hat{\pi}_{jn}(\hat{p}_j, \hat{\boldsymbol{p}}_1, \hat{\boldsymbol{p}}_2, \boldsymbol{x}_1, \boldsymbol{x}_2) = \sum_{n=1}^{\bar{n}} \max_{\boldsymbol{x}_1}[\hat{p}_j\, f(\boldsymbol{x}_1, \boldsymbol{x}_2) - \hat{\boldsymbol{p}}_1\boldsymbol{x}_1 - \hat{\boldsymbol{p}}_2\boldsymbol{x}_2] \qquad (3.1)$$

where, $\hat{\pi}_{jn}$ is the expected profit from choosing alternative $j$ in plot $n$[105], $\hat{p}_j$ is the expected price (own price) of the corresponding alternative, $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$ are vectors of variable (seeds, feed, fertilisers, etc.) and fixed (climate, soils, capital, etc.) inputs respectively, $\hat{\boldsymbol{p}}_1$and $\hat{\boldsymbol{p}}_2$ stand for unit prices of variable and fixed inputs,[106] $f(.)$ represents the production function, and $\bar{n}$ is the total number of plots within the farm.

As the production of crops and livestock takes place under heterogeneous climatic conditions, not all $j$s ensures that an individual farmer will earn the highest profit. Defining the optimal

[105] Alternative $j$ may not be the same between plots within the same farm.
[106] We split the set of inputs into two subsets in order to show below how farmers choose crops or types of livestock taking into account the 'optimal' climate.

climate for alternative $j$ as $T_j^*$ and the actual climate in plot $n$ as $T_n$, farmer $i$ is more likely to choose $j$ as the difference between $T_j^*$ and $T_n$ approaches to zero. Given this condition, equation 3.1 can be rewritten as follows:

$$\sum_{n=1}^{\bar{n}} \hat{\pi}_{ijn}^*\left(\hat{p}_j, \widehat{\boldsymbol{p}}_1, \widehat{\boldsymbol{p}}_2, \boldsymbol{x}_1, \boldsymbol{x}_2^*\right) = \sum_{n=1}^{\bar{n}} \max_{\boldsymbol{x}_1}[\hat{p}_j\, f(\boldsymbol{x}_1, \boldsymbol{x}_2^*) - \widehat{\boldsymbol{p}}_1\boldsymbol{x}_1 - \widehat{\boldsymbol{p}}_2\boldsymbol{x}_2^*] \quad (3.2)$$

where, $\hat{\pi}_{ijn}^*$ denotes the expected profit if $T_j^* - T_n = 0$ or if $T_j^* - T_n$ represents the smallest deviation within the set of available alternatives. So that, if $T_j^* - T_n = 0$, the results from choosing alternative $f$, other than $j$, will not give the farmer the highest profit. In such a case, the decision maker should allocate his land to crop or type of livestock $j$ which better fits $T_n$. Therefore, any modification on the current climate is expected to alter crop and livestock choices.

An individual farmer prefers alternative(s) $j$ over the remaining possibilities if the following condition holds:

$$\sum_{n=1}^{\bar{n}} \hat{\pi}_{ijn}^*\left(\hat{p}_j, \widehat{\boldsymbol{p}}_{x_1}, \widehat{\boldsymbol{p}}_{x_2}, \boldsymbol{x}_1, \boldsymbol{x}_2^*\right) \geq \sum_{n=1}^{\bar{n}} \hat{\pi}_{ifn}\left(\hat{p}_f, \widehat{\boldsymbol{p}}_{x_1}, \widehat{\boldsymbol{p}}_{x_2}, \boldsymbol{x}_1, \boldsymbol{x}_2\right) \quad (3.3)$$

with at least one element in $\boldsymbol{j}$ different from another element in $\boldsymbol{f}$.[107] It is likely that crop and livestock selections within the same farm can be correlated as fixed and variable inputs impose restrictions over the eligible set of alternatives. Even if such correlation exists, equation 3.3 guarantees that agriculturalists maximise their expected joint profits by choosing the combination of agriculture activities that generates the highest value in every plot under their control, that is:

$$argmax\left[\hat{\pi}_{i11}, \hat{\pi}_{i21}, \dots, \hat{\pi}_{iJ1}\right] + argmax\left[\hat{\pi}_{i12}, \hat{\pi}_{i22}, \dots, \hat{\pi}_{iJ2}\right] + argmax\left[\hat{\pi}_{i1\bar{n}}, \hat{\pi}_{i2\bar{n}}, \dots, \hat{\pi}_{iJ\bar{n}}\right] \quad (3.4)$$

Therefore, under current climate conditions farmers choose crops and/or types of livestock that lead to the highest joint expected profit.

[107] These are vectors of alternatives rather than individual options.

### *3.3.2. Method*

To empirically model the previous agriculturalists' behaviour, unordered discrete choice models predict the probability of that a decision-maker chooses any of the alternatives in $A$. Overall, these models indicate that the probability that a farmer $i$ chooses $j$ from a finite set $A = \{1, \ldots, j, \ldots, J\}$ of mutually exclusive alternatives is equal to:

$$Pr_{ijn} = \Pr[y_{in} = j] = F_j(\boldsymbol{s}, \boldsymbol{\theta}), \;\; j = 1, \ldots, J \;\;\; i = 1, \ldots, N \tag{3.5}$$

where, $y_{in} = j$ is the outcome if $j$ is taken, $\boldsymbol{s}$ is a vector of explanatory variables, $\boldsymbol{\theta}$ are the corresponding parameters, and $F_j(.)$ is the functional form of the probability function. Here, $F_j$ has the property to sum over $j$ to one and that probabilities are within the unit interval.

Defining the optimal expected profit as $\hat{\pi}^*_{ijn} = \hat{V}(\boldsymbol{s}_{ijn}) + \varepsilon_{ijn}$, where the first term on the right-hand side is the deterministic part and the second term is the unobserved random component. Among others, Cameron and Trivedi (2005) and Train (2009) argue that $j$ is preferred over the remaining alternatives if and only if $\Pr(\hat{\pi}^*_{ijn} \geq \hat{\pi}_{ifn})$, $\Pr(\hat{\pi}_{ifn} - \hat{\pi}^*_{ijn} \leq 0)$, or $\Pr(\varepsilon_{ifn} - \varepsilon_{ijn} \leq \hat{V}_{ijn} - \hat{V}^*_{ifn})$ for all $f \neq j$[108]. To estimate the set of unknown parameters of the deterministic element, the discrete choice literature partitions $\boldsymbol{s}$ into two different types of variables: $\hat{V}_{ijn} = \boldsymbol{w}'_{ij}\boldsymbol{\beta} + \boldsymbol{z}'_i\boldsymbol{\gamma}_j$, where $\boldsymbol{w}'_{ij}$ and $\boldsymbol{z}'_i$ are *alternative-specific* and *case-specific* explanatory variables. The former type varies across alternatives (price or quality of individual alternatives) while the second type does not (decision-maker's income or age). Regarding the error term, $\varepsilon_{ijn}$, it is known by the farmer, but the econometrician is unable to observe it. Therefore, the functional form of $F_j(.)$ depends on assumptions about the distribution of $\varepsilon_{ijn}$.

[108] Utility is interchanged with profits as it has been done in previous studies using this framework to analyse crop or livestock choices.

The MNL model uses *case-specific* variables to predict the probability that a random farmer chooses alternative $j$ and assumes that elements in $\{\varepsilon_1, \varepsilon_2, \dots, \varepsilon_J\}$ are i.i.d. and follows a type 1 extreme value distribution: $f(\varepsilon_j) = e^{-\varepsilon_j} e^{-e^{-\varepsilon_j}}$. The MNL is defined as follows[109]:

$$Pr_{ij} = \frac{e^{(z_i' \gamma_j)}}{\sum_{l=1}^{J} e^{z_i' \gamma_l}}, \quad j = 1, \dots, J \tag{3.6}$$

The main advantage of the MNL is that the likelihood function is globally concave. Nevertheless, it imposes IIA, that is to say, pairwise comparisons are independent of the existence or exclusion of other alternatives and of their attributes other than the pair under consideration. Hausman (1978) shows that the functional form in (3.6) must satisfy the IIA property, otherwise, the estimated parameters $\boldsymbol{\gamma}_j$ are not valid. Formally, it states that:

$$\Pr(j|\boldsymbol{\gamma}_j, \boldsymbol{z}, C) \equiv \Pr(j|\boldsymbol{\gamma}_j, \boldsymbol{z}, B) * \Pr(B|\boldsymbol{\gamma}_j, \boldsymbol{z}, C) \tag{3.7}$$

where the second term on the right-hand side is equal to $\sum_{j=1}^{J-1} \Pr(j|\boldsymbol{\gamma}_j, \boldsymbol{z}, C)$, $j \in B$, and $B \in C$. Previous studies dealing with the mode of transport, not agricultural issues, claim that the existence of substitution patterns and similarities between alternatives often invalidates condition (3.7) (Domencich and McFadden, 1975; McFadden et al., 1977b; Hausman and Wise, 1978).

Cheng and Long (2007) suggest that violations of the IIA property can be tested through: 1) choice set restrictions and 2) model based tests. On the one hand, the former approach tests IIA using the $H_a$ statistic introduced by Hausman and McFadden (1984). These authors state that estimates that use the full set of alternatives ($\hat{\boldsymbol{\gamma}}^f$) are consistent and efficient under the null but, those estimations using a restricted set of alternatives ($\hat{\boldsymbol{\gamma}}^r$) are inefficient. Thus, the $H_a$ statistic is defined as follows:

[109] For simplicity, we exclude the plot sub index *n*.

$$H_a = (\hat{\boldsymbol{\gamma}}^r - \hat{\boldsymbol{\gamma}}^f)'[\widehat{cov}(\hat{\boldsymbol{\gamma}}^r) - \widehat{cov}(\hat{\boldsymbol{\gamma}}^f)]^{-1}(\hat{\boldsymbol{\gamma}}^r - \hat{\boldsymbol{\gamma}}^f) \tag{3.8}$$

where $[\widehat{cov}(\hat{\boldsymbol{\gamma}}^r) - \widehat{cov}(\hat{\boldsymbol{\gamma}}^f)]$ is the difference between the covariance matrices of $\hat{\boldsymbol{\gamma}}^r$ and $\hat{\boldsymbol{\gamma}}^f$ respectively, and $H_a$ follows a Chi-square distribution with $k$ degrees of freedom.[110] Therefore, systematic differences in $H_a$ indicate that we are unable to reject the alternative hypothesis, and the IIA property does not hold.

On the other hand, we can test IIA by fitting a model that does not impose this restriction. Among other advantages, the NL relaxes this stringent property; it identifies correlation patterns among subsets of alternatives through the estimation of dissimilarity parameters; and its estimation is not subject to the availability of *alternative-specific* variables as the Multinomial Probit model is.[111] For these reasons, the NL is the natural starting point for this analysis.

The NL groups together alternatives according to their similarity and assumes that the error terms within the same group are correlated. In such a case, the IIA property holds within groups but not across them. For simplicity, we describe a two levels nest structure.[112] The full set of elemental alternatives (bottom level) is grouped together into $H$ no overlapping branches (top level) and the payoff from choosing $j$ within branch $h$ is equal to $V_{hj} + \varepsilon_{hj}$, where $j = 1, \dots, J_h$, $h = 1, \dots, H$ and the total number of alternatives is $J_1 + J_2 + \cdots + J_H = J$. Thus, the probability of choosing $j$ within branch $h$ is defined as follows:

$$Pr_{hj} = Pr_h * Pr_{j|h} = \underbrace{\frac{e^{(\boldsymbol{z}'\boldsymbol{\alpha}_h + \lambda_h \boldsymbol{I}_h)}}{\sum_{l=1}^{H} e^{(\boldsymbol{z}'\boldsymbol{\alpha}_l + \lambda_l \boldsymbol{I}_l)}}}_{Top\ equation} * \underbrace{\frac{e^{(\tilde{\boldsymbol{z}}'\boldsymbol{\beta}_{jh}/\lambda_h)}}{\sum_{o=1}^{J_h} e^{(\tilde{\boldsymbol{z}}'\boldsymbol{\beta}_{oh}/\lambda_h)}}}_{Bottom\ equation} \tag{3.9}$$

[110] It has been argued that $H_a$ sometimes fails to satisfy asymptotic properties as $[\widehat{cov}(\hat{\boldsymbol{\gamma}}^r) - \widehat{cov}(\hat{\boldsymbol{\gamma}}^f)]$ is a poor estimator of $cov(\hat{\boldsymbol{\gamma}}^r - \hat{\boldsymbol{\gamma}}^f)$. Alternatively, we can obtain a valid estimator through the following expression: $\widehat{var}(\hat{\boldsymbol{\gamma}}^r) - cov(\hat{\boldsymbol{\gamma}}^r, \hat{\boldsymbol{\gamma}}^f) - cov(\hat{\boldsymbol{\gamma}}^f - \hat{\boldsymbol{\gamma}}^r) + \widehat{var}(\hat{\boldsymbol{\gamma}}^f)$, which has the advantage over the classical test of allowing econometricians to cluster data and to obtain efficient estimators.

[111] The Multinomial Probit model also relaxes the IIA assumption computing a correlation matrix for individual alternatives. Nevertheless, the estimation of this model is subject to the availability of *alternative- specific* regressors. Additionally, it does not have a closed solution and the complexity of its computation dramatically rises as the number of alternatives increases.

[112] See Train, 2009, pp. 86-88 for an example of a three-level model.

where $\boldsymbol{\alpha}_h$ vary over branches and $\boldsymbol{\beta}_{jh}$ vary over both branches and individual alternatives. The relationship between both equations in (3.9) is captured by the *inclusive value*, which is defined as follows:

$$\boldsymbol{I}_h = \ln\left(\sum_{o=1}^{J_h} e^{\left(\frac{\tilde{z}'\beta_{oh}}{\lambda_h}\right)}\right) \quad (3.10)$$

where $\lambda_h$ is the dissimilarity parameter of branch $h$. This coefficient measures the correlation among error terms within the same branch. Cameron and Trivedi (2005) states that $\lambda_h = \sqrt{1 - cor(\varepsilon_{hj}, \varepsilon_{hl})}$. Thus, $\lambda_h = 1$ implies zero correlation between alternatives and the appropriateness of the MNL.[113] Conversely, $0 < \lambda_h < 1$ indicates some degree of correlation. In such a case, parameters in the bottom equation must be rescaled using $\lambda_h$.

The dissimilarity parameters also help us to test whether the NL is consistent with farmers' maximisation behaviour. To be aligned with the Random Utility Model (RUM), these coefficients must range within the unit interval (Cameron and Trivedi, 2005; Train, 2009). There exist some examples in the existing literature in which $\lambda_h > 1$, in such cases the NL is consistent for a certain range of values of the explanatory variables and the proposed nest structure may not be well designed (Train et al., 1987; Kling and Herriges, 1995; Herriges and Kling, 1996; Lee, 1999). Although $\lambda_h < 0$ is mathematically possible, negative values imply that decision-makers choose those branches that do not lead to the highest expected profits.

Parameters in the NL can be estimated by using the Full Information Maximum Likelihood (FIML) or the Limited Information Maximum Likelihood (LIML) methods. The former approach maximises the log-likelihood function with respect to $\boldsymbol{\alpha}_h$, $\boldsymbol{\beta}_{jh}$, and $\lambda_h$ simultaneously. However, the convergence of the FIML estimator is not guaranteed as the likelihood function may not be globally concave. Furthermore, the complexity of its estimation

[113] Thus, the MNL is a particular case of the NL model.

rises as the number of alternatives increases. In such cases, the LIML method should be applied. According to Greene (2000), the LIML estimator uses a *bottom-up* two-step maximum likelihood procedure, which is as follows:

1. estimate $\boldsymbol{\beta}_{jh}/\lambda_h$ by fitting a MNL model to predict the probability of choosing alternative $j$ within branch $h$, and
2. compute the inclusive values for all branches in the upper level, then estimate $\boldsymbol{\alpha}_h$ and $\lambda_h$ using a Conditional Logit (CL) model to predict the probability of choosing branch $h$ given attributes $\boldsymbol{z}$ and $\boldsymbol{I}_h$.

By doing this, we can recover $\widehat{\boldsymbol{\beta}}_{jh}$ multiplying the first-stage parameter $\widehat{\boldsymbol{\beta}}_{jh}/\hat{\lambda}_h$ times the scale parameter, $\hat{\lambda}_h$[114].

### *3.3.3. Data*

Seeking to overcome deficiencies in previous studies this research uses two new cohorts of cross-sectional data in Mexico. The National Institute of Statistics and Geography (INEGI by its acronym in Spanish), through the National Agricultural Survey (NAS), collects data on agricultural and livestock activities. These databases are representative samples of the 31 major commodities in the 2012 and 2014 agricultural years. Unlike previous analyses, these datasets report farmers' choices at the plot-level rather than the 'primary' activity per farm for both arable and non-arable activities. Therefore, the dependent variable in the empirical models is defined as the crop grown or type of livestock raised in each plot in the corresponding year.[115]

Both NAS-2012 and NAS-2014 report actual choices in 258,217 and 202,338 plots respectively. Survey respondents were able to identify the Control Area (CA)[116] for their respective plots as questionnaires were complemented with printed or digital maps. However, some of these

[114] Refer to Heiss et al. (2002) and Hensher and Greene (2002) for a further discussion about the scale parameter.
[115] From October to September of the corresponding periods: 2011-2012 and 2013-2014 respectively.
[116] Identifying the specific location of these fields is crucial. INEGI divides the entire territory of Mexico into 32 states, disaggregating them further into 2,437 municipalities, which at the same time circumscribe 17,409 Geo-statistical areas (AGEBs). These zones are finally partitioned into 295,141 control areas (CA).

records are excluded from the sample due to missing values, lack of geographical location codes, or because the respondent reports a choice other than the 31 mutually exclusive commodities. Thus, the discrete choice models use 219,985 and 168,265 valid observations respectively.

According to the Indicative Crop Classification 2010 (ICC-2010) elaborated by the Food and Agriculture Organization (FAO), we can group 28 of the 31 products into five categories: beverage crops, cereals, fruits, vegetables, and other crops[117] (FAO, 2006). The remaining three alternatives are livestock activities. Figures 3.2a and 3.2b show the geographical distribution of the observed choices. Overall, we do not observe remarkable differences between the geographical distribution of the 2012 and 2014 samples.[118]

**Figure 3.2 Plot-level observed choices**

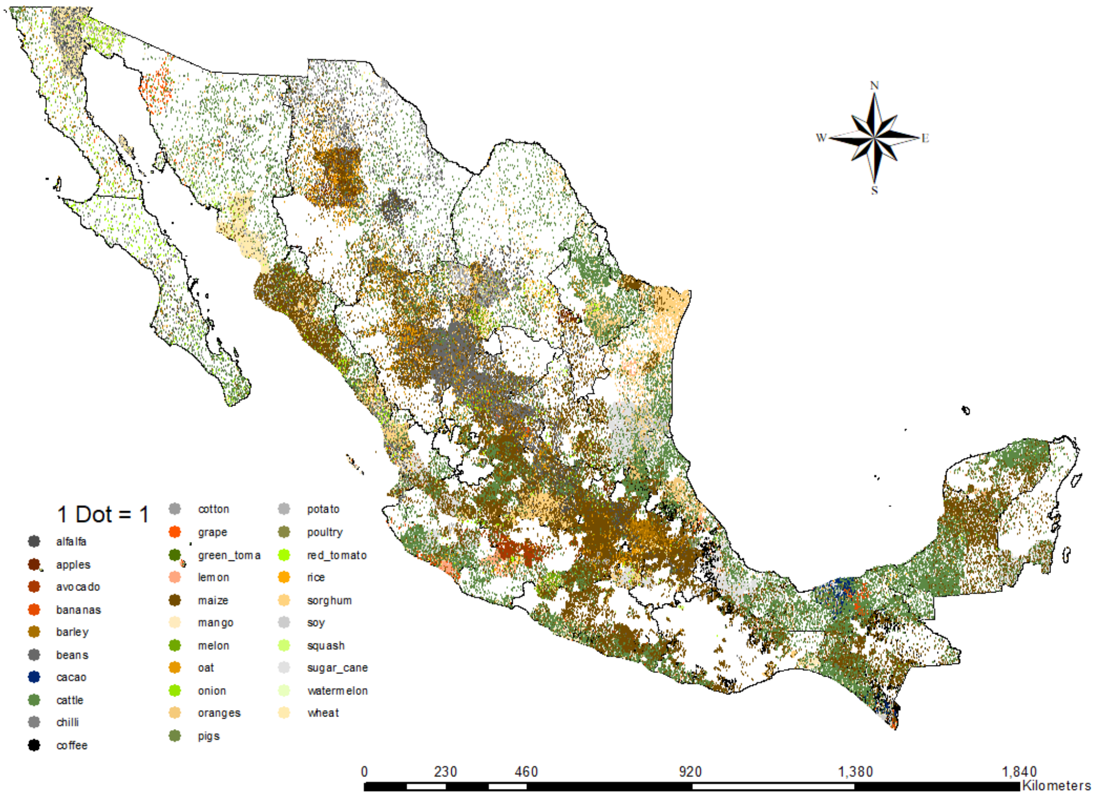



**Figure 3.2a Plots and choices 2012 (1 dot=1 plot-choice)**

[117] This subset includes those alternatives that after grouping other commodities were the only crops within a single category.
[118] Not all farms in NAS-2012 were surveyed in the NAS-2014, so, we cannot treat this information as panel data.

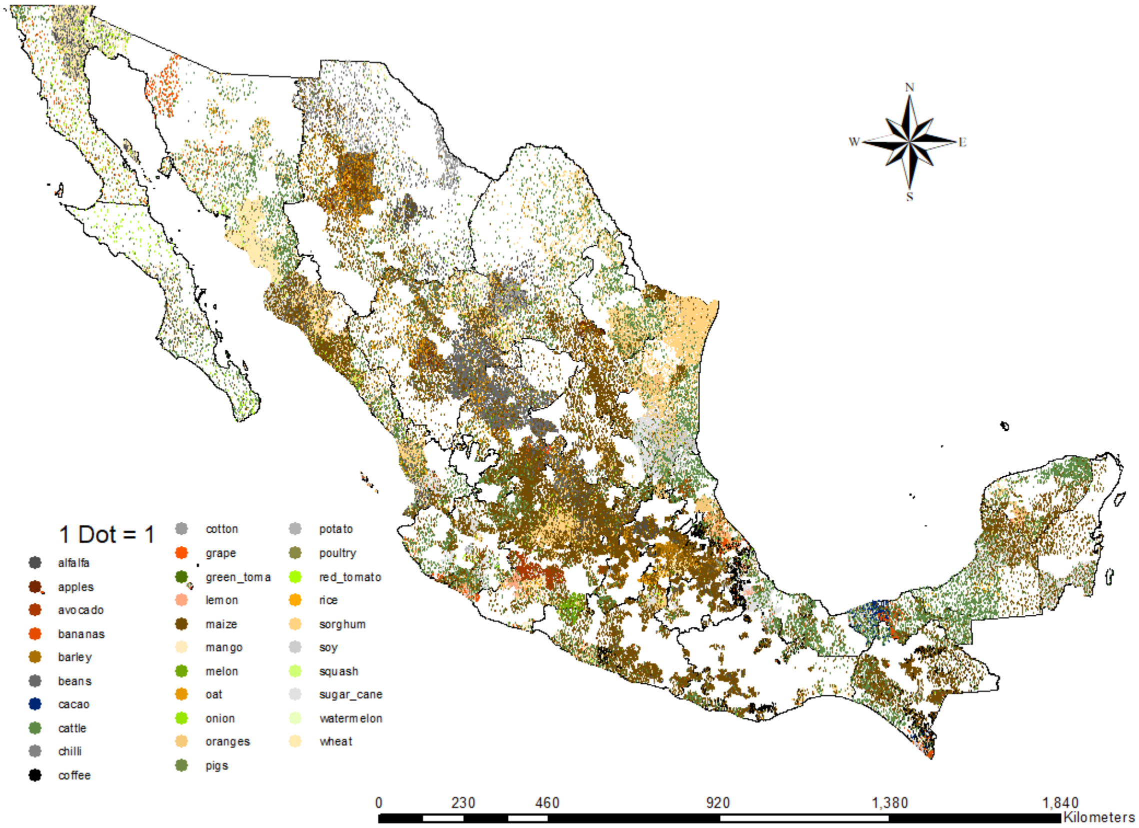



**Figure 3.2b Plots and choices 2014 (1 dot=1 plot-choice)**

Using the CA's code and treating climate as a given fixed input, we assign the long-term average (normal) of temperature and rainfall to all plots within the same CA. To obtain these values we use the highest resolution Geographical Information System (GIS)-databases available up to date (~1km$^2$ at the equator), published by Hijmans et al. (2005), to compute the 1950-2000 averages of daily mean temperature and rainfall over all square kilometres within a CA. [119] Using the same GIS-databases, we assign the long-term standard deviation of temperature and the coefficient of variation of rainfall to the corresponding plots.

As each farmer maximises expected profits at the beginning of each agricultural year, we introduce expected output and input prices into the analysis. The Secretariat of Agriculture, Livestock and Rural Development, Fisheries and Food (SAGARPA by its acronym in Spanish)

[119] We follow the same procedure as in Chapter 2 to obtain temperature and rainfall of the corresponding CAs.

publishes annual reports on more than 300 commodities, which contains the average farm-gate price of each product at the municipality level. Thus, we add the corresponding 31 average prices from the previous 5 years using Fisher price indices[120] to the database. To obtain parameter estimates of the corresponding profit functions, one would desire information on fixed and variable input prices such as tractors, equipment, fertilisers, and other inputs. Despite this data is available, there is not enough variation on these prices as a few number of firms control these markets therefore, we assume that Mexican agriculturalists face the same cost per unit of capital and all other non-labour costs. Conversely, the cost per unit of labour may differ from one market to another. Using data on both NAS-2012 and NAS-2014, we divide labour expenses per farm by the total number of working hours in the corresponding year. As some farmers may misreport total labour expenses, because of sporadic hiring, we calculate the average wage rate per municipality. Plot size also enters into the choice equations as a quasi-fixed input which is considered as something not modifiable in the short-run by the farmer, especially in the same agricultural year.

Some fields may be unsuitable for particular agricultural activities. Physical and chemical characteristics of the soil such as levels of organic matter, salinity, water holding capacity, pH levels, and other features could deter farmers from planting or raising specific crops or types of livestock. Following the *World reference base for soil resources* (FAO, 1994), INEGI publishes a GIS-database that classifies land into 21 soil types taking into account a wide range of physical and chemical characteristics of the soil. Intersecting the GIS-databases of soils and CAs, we obtain soil types as percentages of the total area for each CA in both samples. Not all

[120] This index reflects the relative change of a set of prices at time $t_1$ with respect to time $t_0$ or the base year and it is given by the following expression:

$$P_{j,t_1} = \sqrt{\frac{\Sigma(\bar{p}_{j,t_1} * Q_{j,t_1})}{\Sigma(\bar{p}_{j,t_0} * Q_{j,t_1})} * \frac{\Sigma(\bar{p}_{j,t_1} * Q_{j,t_0})}{\Sigma(\bar{p}_{j,t_0} * Q_{j,t_0})}}$$

where $\bar{p}_{j,t_1}$ stands for the average price of item $j$ either for the 2007-2011 or 2009-2013 periods; $\bar{p}_{j,t_0}$ is the average price for the base period; $Q_{j,t_0}$ and $Q_{j,t_1}$ represent the total output for the corresponding items and periods. The Central Bank of Mexico and INEGI use 2002-2003 prices as the base year for consumer index and inflation calculations arguing that it was a period of relative stability and we do not find a different trend in the 2004-2006 period, therefore we calculate the Fisher index using 2002-2006 average as the base period.

soil profiles are included in the analysis because only four types characterise 70% of the total sampled lands. Moreover, we exclude the remaining soils to avoid high collinearity among these variables. The discrete choice modelling literature suggests the inclusion of socio-demographic characteristics of the decision-maker, therefore, we account for age, education, and ethnicity in the empirical analysis. Additionally, we include as dummy variables the farmer's possession of a mobile phone and access to internet, the Euclidian distance from each plot to the nearest urban area and road density in order to account for access to markets and information.

After signing the North American Free Trade Agreement (NAFTA) in 1993, the Mexican government subsidises agriculture through the *'Programa de Apoyos Directos al Campo'* (PROCAMPO) per unit of cultivated land to reduce the productivity gap between local and producers in Canada and United States of America (USA). Initially, farmers growing cotton, rice, safflower,[121] barley, beans, maize, sorghum, soy, and wheat were able to enrol their lands into this programme but since 1995, beneficiaries can cultivate any legal crop. The *'PROGAN productivo'* (PROGAN) programme is also a direct cash transfer to farmers who allocate their production efforts to beef cattle, sheep, goats, bees, or pig breeding activities and pays a certain amount per head. Unfortunately, this information is only reported in the NES-2014. Table 3.9 in Appendix A3.2 displays definitions, units, and distributions of the set of variables included in the empirical analysis.

## 3.4. Results and discussion

To investigate the effects of climate on crop and type of livestock choices we estimate different MNL and NL models. Regarding the latter type of model, the existing literature does not provide a widely accepted method to identify the optimal nest structure. Among others,

[121] Farmers cultivate safflower to obtain vegetable oil from the seeds.

Cameron and Trivedi (2005) suggest that the existence of a natural classification criterion facilitates the application of the NL. Small and Brownstone (1982) and Herriges and Kling (1997) argue that we can discard those models for which the dissimilarity parameters lie out of the unit interval. Alternatively, we can estimate a non-nested model, that is to say the MNL, then introduce different nest structures sequentially and use the Akaike or Bayesian Information Criteria (Schwiebert, 2015) or the likelihood dominance criterion (Herriges and Kling, 1997; Huang and Zhao, 2015) to discriminate between different specifications.

As there exists a natural classification of agricultural commodities in our case study, we use the *Indicative Crop Classification Version 1.0* elaborated by the Food and Agriculture Organisation (FAO, 2006) to design the nest structure. Figures 3.3 and 3.4 display the nest structures of the MNL and NL using the abovementioned aggregation. To analyse individual commodities, we use the nest structures shown in Figures 3.5 and 3.6. Thus, these nesting structures allow us to estimate seven different dissimilarity parameters to evaluate the appropriateness of the models.[122]

[122] We first assume equality of dissimilarity parameters of crops and livestock activities, and then we relaxed this assumption in those models that include individual alternatives.

**Figure 3.3 Multinomial Logit model (groups)**

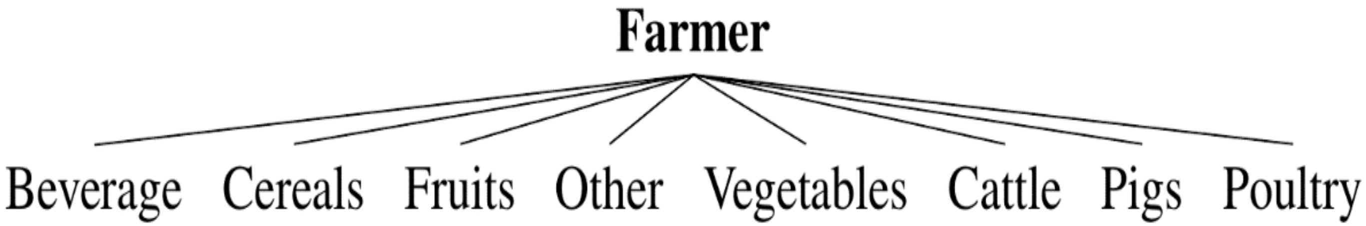



**Figure 3.4 Nested Logit model (groups)**

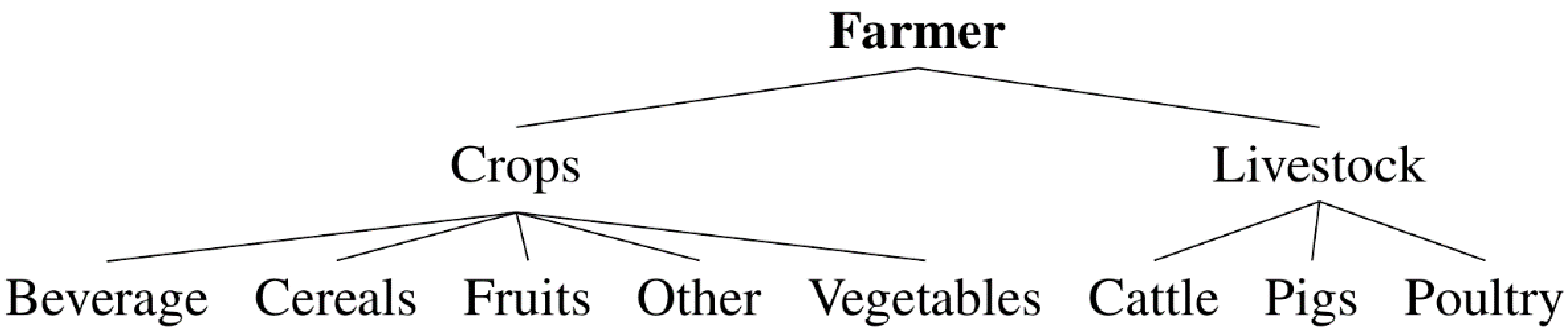


**Figure 3.5 Multinomial Logit model (individual alternatives)**

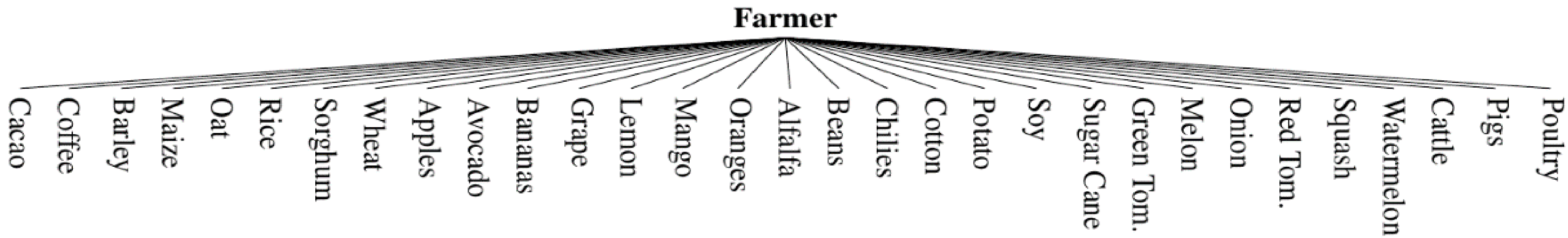
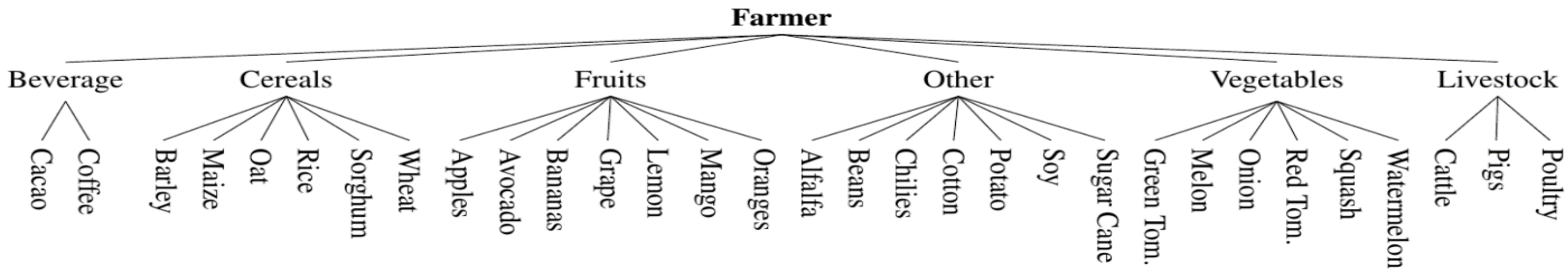



**Figure 3.6 Nested Logit model (individual alternatives)**



### *3.4.1. Multinomial Logit model*

Tables 3.1 and 3.2 show the results of the MNL displayed in Figure 3.3.[123] We estimate separate models for the 2012 and 2014 samples. We define cereals as the base category[124] then a positive (negative) regression parameter means that, relatively to cereals, the probability of choosing the corresponding alternative rises (decreases) as the $k$-th explanatory variable increases. Given the complexity of the estimation of MNL and NL models with several alternatives and the fact that predictions about the future climate in the same GIS-databases are only available in annual figures, we use annual temperature and rainfall in the set of discrete models.

To identify the influence of climate on crop and livestock choices we use linear, square, and interaction terms of annual temperature and rainfall. The standard deviation of temperature and the coefficient of variation of rainfall are also included in the analysis as agronomists and vets argue that heat/humidity stress may harm crops and livestock. The results from the MNL suggest that climate in fact drives agriculturalists' production decisions and the existence of a nonlinear effect of climate on farmers' choices, which corroborates previous findings. There exists a hill-shape or U-shape relationship between climate and the probability of choosing a particular commodity. In line with Fezzi and Bateman (2015), we encounter significant positive nonlinear interaction effects suggesting that higher volumes of rainfall may reduce harmful effects of heat stress. This effect has been ignored in the surveyed literature and may be distorting climate effects over crop and livestock choices.

Equation 3.2 in section 3.3.1 shows that prices of other alternatives (cross-prices) are not arguments of the corresponding expected profit function then, we set regression coefficients of

[123] Tables 3.13-3.18 in Appendix A3.2 show the results of the 31-alternatives MNL models.
[124] To estimate a MNL model, we need this normalisation ($\boldsymbol{\gamma_{cereals}} = \mathbf{0}$). Such normalisation guarantees that the probabilities sum to one.

cross-prices to zero.[125] This restriction does not ignore cross-prices, as these values appear in the denominator of equations (3.6) and (3.9). Our findings are not entirely in line with theoretical expectations as the own-price coefficients of beef cattle and pigs are not positive, which suggests that farmers choose these options more often when the price is lower. This result may be attributable to omitted variables as has been found in previous studies (Kurukulasuriya and Mendelsohn, 2008; Seo et al. 2008b). Aside from omitted variables, farmers might weigh output prices from more recent years more heavily. The remaining set of own-prices shows the correct signs; prices that grew faster in the previous 5 years incline agriculturalists towards those activities.

Examining the coefficients on the wage rate one can observe that the odd-ratios differ across time. For the 2012 sample, farmers tend to choose alternatives other than cereals as the cost of labour rises. In contrast, using the 2014 sample we observe the opposite effects, except for other crops and vegetables. Although, there is not a clear explanation about the positive effect of wage rates, this effect may arise due to measurement errors as some farmers may misreport total labour expenses in the survey and the calculation of average rates at the municipality level may not be reflecting the relevant wage rate. Those coefficients that are not statistically significant may capture high dependency on unpriced family labour. Regarding the size of the plot, the results show that farmers are less likely to select beef cattle in small fields where they prefer less (land) intensive commodities such as beverage crops or vegetables. This finding meets our prior beliefs since the production of beef cattle typically takes place in extensive pastures.

Socio-demographic characteristics greatly influence farmers' decisions. We find that the age of farmer increases the willingness to move their production efforts from cereals to beverage crops, beef cattle, and fruits, while younger producers often choose poultry and vegetables. The

[125] Tables 3.10 and 3.11 in Appendix A3.2 show the results of the unrestricted MNL model.

years of study also increase the probability to move away from cereals in favour of other activities. Conversely, farmers that recognise themselves as members of an indigenous community are reluctant to modify their production decisions. Indeed, native communities are recognised for their efforts to preserve older varieties of maize.

Crop and livestock choices are sensitive to market accessibility and the ability to access information. The possession of a mobile phone lead to movements away from cereals in favour of fruits, other crops, and pigs while its effect is not conclusive for cattle and poultry. Access to the internet reinforces this effect and promotes the production of fruits, pigs, poultry and vegetables. The results for these two indicators may reveal that access to information incentivizes farmers to choose non-traditional agricultural activities, as they may be aware of the attributes of other alternatives. Tables 3.1 and 3.2 also suggest that the closer the plot to the local market, the higher the probability of choosing beverage crops, fruits and other crops. Because of the Mexican civil war in 1910, large properties known as 'haciendas' and 'latifundios' were re-distributed among smallholders and communities throughout the so-called 'ejidal' or 'communal' lands. These areas are generally far away from the urban areas and extensive beef cattle production typically takes place in those zones. In some cases, the Euclidean distance between the plot and the nearest city may not precisely reflect proximity as we observe complex terrains in the sampled agricultural areas therefore road density aims to capture this complexity. In this regard, beverage crops and poultry activities are preferred in municipalities with higher density. One may argue that these variables are redundant in the model as farm gate prices account for transport costs. However, this is not necessarily true. There might be some prices that do not vary across large areas therefore such prices do not necessarily capture the heterogeneity of transport costs and transportation times, which are very important for perishable commodities. Under such circumstances, the Euclidean distance and the road density variables aim to capture such heterogeneity.

Physical and chemical characteristics of the soil facilitate or prevent the productions of particular crops or livestock. Tables 3.1 and 3.2 show that beef cattle, fruits, and vegetables are preferred in areas classified as Feozem and Regosol types. Any other soil type deters the production of any of the alternatives other than cereals. The lack of data on subsidies in the NAS-2012 prevents us to identify the farmers' choices-subsidies relationship in 2012. To be consistent with the set of estimations in this chapter, we estimate the MNL model for the 2012 and 2014 samples without subsidy payments (see Tables 3.1 and 3.2) and show the estimation with subsidy payments in Table 3.12 in Appendix A3.2. Although the Mexican government claims that PROCAMPO and PROGAN do not distort the market either via prices or outputs (SAGARPA, 2018), it is clear from the results in Table 3.12 that these cash transfers do indeed modify agriculturalists' production decisions. These payments seem to guide farmers' decisions by preventing them to move away from traditional choices as these subsidies may offset the gains from switching to a more profitable activity.

## Table 3.1 Multinomial Logit model 8 alternatives (2012)

| VARIABLES | beverage | cattle | cereals | fruits | other | pigs | poultry | vegetables |
|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | |
| Temperature | 3.2912*** | 0.7407*** | | -0.5459*** | 0.9078*** | -0.3746 | 2.5181*** | 0.9718*** |
| | (0.1540) | (0.0397) | | (0.0461) | (0.0660) | (0.4505) | (0.3741) | (0.3381) |
| Temperature sq. | -0.0763*** | -0.0188*** | | 0.0171*** | -0.0301*** | 0.0065 | -0.0664*** | -0.0229** |
| | (0.0037) | (0.0010) | | (0.0011) | (0.0021) | (0.0089) | (0.0097) | (0.0093) |
| Rainfall | 0.8070*** | -0.0314 | | 0.6805*** | -1.0475*** | -0.1258 | -0.6331*** | -0.9352*** |
| | (0.0469) | (0.0308) | | (0.0412) | (0.0569) | (0.4492) | (0.2260) | (0.1506) |
| Rainfall sq. | -0.0176*** | -0.0106*** | | -0.0145*** | -0.0086*** | -0.0137 | -0.0120** | 0.0038** |
| | (0.0006) | (0.0004) | | (0.0009) | (0.0008) | (0.0094) | (0.0060) | (0.0017) |
| Temp.*Rainfall | 0.0039* | 0.0201*** | | -0.0037** | 0.0573*** | 0.0177 | 0.0391*** | 0.0299*** |
| | (0.0020) | (0.0014) | | (0.0018) | (0.0031) | (0.0161) | (0.0111) | (0.0077) |
| Temperature SD | -0.0944*** | 0.0037** | | 0.0336*** | 0.0287*** | -0.0216 | -0.0396*** | -0.0217*** |
| | (0.0059) | (0.0018) | | (0.0031) | (0.0016) | (0.0211) | (0.0151) | (0.0065) |
| Rainfall seasonality | -0.0120*** | -0.0115*** | | 0.0021 | -0.0006 | 0.0034 | -0.0162** | -0.0022 |
| | (0.0026) | (0.0010) | | (0.0021) | (0.0017) | (0.0059) | (0.0067) | (0.0026) |
| **Output prices** | | | | | | | | |
| Price beverage | -0.0009 | | | | | | | |
| | (0.0011) | | | | | | | |
| Price cattle | | -0.0165*** | | | | | | |
| | | (0.0013) | | | | | | |
| Price fruits | | | | 0.0177*** | | | | |
| | | | | (0.0019) | | | | |
| Price other | | | | | 0.0287*** | | | |
| | | | | | (0.0018) | | | |
| Price pigs | | | | | | -0.0236*** | | |
| | | | | | | (0.0082) | | |
| Price poultry | | | | | | | 0.0196*** | |
| | | | | | | | (0.0070) | |
| Price vegetables | | | | | | | | 0.0090*** |
| | | | | | | | | (0.0028) |
| **Inputs** | | | | | | | | |
| Wage rate | 0.0014 | 0.0040*** | | 0.0075*** | -0.0011 | 0.0117*** | 0.0074*** | 0.0093*** |
| | (0.0012) | (0.0006) | | (0.0007) | (0.0007) | (0.0033) | (0.0022) | (0.0019) |
| Plot size | -0.0849*** | 0.6235*** | | 0.0520*** | -0.0083 | 0.0520 | 0.2051*** | -0.1067*** |
| | (0.0240) | (0.0116) | | (0.0166) | (0.0097) | (0.0599) | (0.0532) | (0.0259) |
| **Socio-demographic characteristics** | | | | | | | | |
| Age | 0.0146*** | 0.0121*** | | 0.0148*** | 0.0020 | 0.0026 | -0.0222*** | -0.0153*** |
| | (0.0026) | (0.0014) | | (0.0023) | (0.0019) | (0.0096) | (0.0079) | (0.0032) |
| Indigenous | -1.0016*** | -1.0209*** | | -0.8255*** | -1.3353*** | -0.3457 | -2.8597*** | -1.4539*** |
| | (0.0851) | (0.0513) | | (0.0766) | (0.0653) | (0.3310) | (1.0235) | (0.1966) |
| Schooling | 0.0169** | 0.0313*** | | 0.0456*** | 0.0308*** | 0.1801*** | 0.1447*** | -0.0130 |
| | (0.0084) | (0.0053) | | (0.0076) | (0.0046) | (0.0408) | (0.0329) | (0.0112) |
| **Access to markets** | | | | | | | | |
| Mobile | -0.0284 | -0.0563 | | 0.4898*** | 0.0938** | 0.4673** | 0.8407** | 0.0311 |
| | (0.1402) | (0.0406) | | (0.0589) | (0.0421) | (0.1934) | (0.3284) | (0.0910) |
| Internet | -0.0633 | -0.3773*** | | 0.2201* | 0.0621 | 1.7905*** | 1.1925*** | 0.6083*** |
| | (0.2300) | (0.0842) | | (0.1300) | (0.1161) | (0.1726) | (0.2856) | (0.1411) |
| City | -0.0517*** | 0.0171*** | | -0.0395*** | -0.0197*** | -0.0040 | -0.0284 | 0.0182** |
| | (0.0062) | (0.0020) | | (0.0038) | (0.0024) | (0.0137) | (0.0178) | (0.0081) |
| Road density | 2.0278*** | -0.6316*** | | -1.5645*** | -1.0753*** | -0.1338 | 0.7857** | -0.2426 |
| | (0.1473) | (0.0786) | | (0.1355) | (0.0838) | (0.4577) | (0.3494) | (0.2507) |
| **Soils** | | | | | | | | |
| Vertisol | -0.0208*** | -0.0064*** | | -0.0049*** | -0.0047*** | -0.0166*** | -0.0091*** | -0.0045*** |
| | (0.0021) | (0.0006) | | (0.0009) | (0.0005) | (0.0026) | (0.0030) | (0.0013) |
| Feozem | -0.0117*** | 0.0029*** | | 0.0064*** | -0.0021*** | -0.0083** | 0.0054** | -0.0006 |
| | (0.0018) | (0.0005) | | (0.0008) | (0.0005) | (0.0034) | (0.0027) | (0.0013) |
| Regosol | -0.0085*** | 0.0050*** | | -0.0021* | -0.0027*** | -0.0140*** | -0.0140*** | 0.0077*** |
| | (0.0011) | (0.0005) | | (0.0013) | (0.0010) | (0.0034) | (0.0040) | (0.0017) |
| Cambisol | -0.0102*** | -0.0026*** | | -0.0091*** | -0.0076*** | -0.0265*** | -0.0022 | -0.0004 |
| | (0.0010) | (0.0006) | | (0.0012) | (0.0009) | (0.0055) | (0.0074) | (0.0021) |
| Constant | -42.9290*** | -9.8133*** | | -7.0111*** | -11.4546*** | -1.4719 | -30.7126*** | -11.2510*** |
| | (1.6480) | (0.4022) | | (0.5866) | (0.4938) | (6.9881) | (4.0009) | (3.0211) |
| Observations | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 |

Robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: cereals. SD: Standard Deviation.

## Table 3.2 Multinomial Logit model 8 alternatives (2014)

| VARIABLES | beverage | cattle | cereals | fruits | other | pigs | poultry | vegetables |
|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | |
| Temperature | 3.4955*** | 0.7598*** | | -0.7249*** | 0.5094*** | 0.0280 | 0.9130** | 0.4843* |
| | (0.1584) | (0.0656) | | (0.0495) | (0.0946) | (0.6036) | (0.4283) | (0.2805) |
| Temperature sq. | -0.0815*** | -0.0215*** | | 0.0200*** | -0.0216*** | -0.0020 | -0.0251** | -0.0111 |
| | (0.0038) | (0.0017) | | (0.0012) | (0.0030) | (0.0111) | (0.0109) | (0.0082) |
| Rainfall | 0.8103*** | -0.3249*** | | 0.4793*** | -1.4379*** | 0.0326 | -0.1854 | -0.6935*** |
| | (0.0632) | (0.0486) | | (0.0489) | (0.0795) | (0.6503) | (0.1777) | (0.1645) |
| Rainfall sq. | -0.0170*** | -0.0116*** | | -0.0151*** | -0.0043*** | -0.0172 | -0.0113** | 0.0053** |
| | (0.0007) | (0.0006) | | (0.0011) | (0.0010) | (0.0111) | (0.0048) | (0.0021) |
| Temp.*Rainfall | 0.0022 | 0.0337*** | | 0.0033* | 0.0675*** | 0.0126 | 0.0256*** | 0.0182** |
| | (0.0023) | (0.0020) | | (0.0018) | (0.0041) | (0.0218) | (0.0087) | (0.0087) |
| Temperature SD | -0.0918*** | 0.0112*** | | 0.0459*** | 0.0200*** | -0.0456 | -0.0034 | -0.0452*** |
| | (0.0055) | (0.0021) | | (0.0026) | (0.0027) | (0.0278) | (0.0248) | (0.0089) |
| Rainfall seasonality | -0.0055** | -0.0028*** | | -0.0122*** | 0.0040** | 0.0034 | 0.0029 | 0.0124*** |
| | (0.0026) | (0.0010) | | (0.0019) | (0.0018) | (0.0050) | (0.0072) | (0.0032) |
| **Output prices** | | | | | | | | |
| Price beverage | 0.0039** | | | | | | | |
| | (0.0016) | | | | | | | |
| Price cattle | | -0.0039*** | | | | | | |
| | | (0.0015) | | | | | | |
| Price fruits | | | | 0.0146*** | | | | |
| | | | | (0.0012) | | | | |
| Price other | | | | | 0.0202*** | | | |
| | | | | | (0.0032) | | | |
| Price pigs | | | | | | -0.0179** | | |
| | | | | | | (0.0073) | | |
| Price poultry | | | | | | | 0.0186 | |
| | | | | | | | (0.0125) | |
| Price vegetables | | | | | | | | -0.0005 |
| | | | | | | | | (0.0037) |
| **Inputs** | | | | | | | | |
| Wage rate | -0.0095*** | -0.0009 | | -0.0004 | 0.0019* | 0.0028 | -0.0108* | 0.0061* |
| | (0.0026) | (0.0017) | | (0.0013) | (0.0011) | (0.0079) | (0.0061) | (0.0033) |
| Plot size | -0.0691*** | 0.4913*** | | -0.0403** | -0.0052 | 0.0426 | 0.0793 | -0.0603** |
| | (0.0195) | (0.0160) | | (0.0171) | (0.0092) | (0.0513) | (0.0924) | (0.0276) |
| **Socio-demographic characteristics** | | | | | | | | |
| Age | 0.0165*** | 0.0186*** | | 0.0182*** | 0.0012 | 0.0078 | 0.0189 | -0.0133*** |
| | (0.0024) | (0.0014) | | (0.0023) | (0.0014) | (0.0057) | (0.0128) | (0.0038) |
| Indigenous | -0.6225*** | -0.3969*** | | 0.0216 | -0.0905* | -0.0256 | -0.1522 | -0.1873 |
| | (0.0766) | (0.0564) | | (0.0565) | (0.0516) | (0.1954) | (0.3394) | (0.1337) |
| Schooling | 0.0348*** | 0.0356*** | | 0.0451*** | 0.0141** | 0.0147 | 0.0242 | -0.0046 |
| | (0.0088) | (0.0050) | | (0.0072) | (0.0069) | (0.0236) | (0.0340) | (0.0140) |
| **Access to markets** | | | | | | | | |
| Mobile | -0.3235*** | 0.2970*** | | 0.2341*** | 0.3624*** | 0.6704*** | -0.0771 | 0.1293 |
| | (0.0980) | (0.0416) | | (0.0576) | (0.0386) | (0.1975) | (0.2768) | (0.1582) |
| Internet | 0.1358 | -0.1895** | | 0.4038*** | 0.2004* | 2.1566*** | 2.0696*** | 1.0486*** |
| | (0.2541) | (0.0960) | | (0.1153) | (0.1126) | (0.3286) | (0.4457) | (0.1468) |
| City | -0.0591*** | 0.0184*** | | -0.0547*** | -0.0102*** | -0.0305* | 0.0050 | 0.0257*** |
| | (0.0053) | (0.0024) | | (0.0039) | (0.0022) | (0.0178) | (0.0202) | (0.0096) |
| Road density | 2.0516*** | -0.8711*** | | -1.0028*** | -1.1740*** | -1.1190* | 0.8495 | -0.4252 |
| | (0.1231) | (0.1312) | | (0.1246) | (0.1064) | (0.6732) | (0.5190) | (0.2980) |
| **Soils** | | | | | | | | |
| Vertisol | -0.0183*** | -0.0047*** | | -0.0030*** | -0.0035*** | -0.0147*** | -0.0177*** | -0.0031** |
| | (0.0014) | (0.0007) | | (0.0008) | (0.0008) | (0.0020) | (0.0036) | (0.0015) |
| Feozem | -0.0121*** | 0.0030*** | | 0.0060*** | -0.0012* | -0.0069 | -0.0075* | 0.0031* |
| | (0.0015) | (0.0006) | | (0.0009) | (0.0007) | (0.0048) | (0.0041) | (0.0017) |
| Regosol | -0.0064*** | 0.0061*** | | 0.0016 | 0.0013 | -0.0123*** | -0.0051 | 0.0137*** |
| | (0.0011) | (0.0006) | | (0.0012) | (0.0012) | (0.0036) | (0.0034) | (0.0020) |
| Cambisol | -0.0024*** | -0.0031*** | | -0.0041*** | -0.0052*** | -0.0276*** | -0.0024 | 0.0001 |
| | (0.0009) | (0.0007) | | (0.0012) | (0.0011) | (0.0065) | (0.0086) | (0.0023) |
| Constant | -45.8794*** | -11.9898*** | | -2.8859*** | -5.9501*** | -3.1306 | -20.2744*** | -6.6391*** |
| | (1.8801) | (0.5827) | | (0.6378) | (0.4934) | (10.9448) | (5.1672) | (2.4212) |
| Observations | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 |

Robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: cereals. SD: Standard Deviation.

Turning the discussion into the validity of the IIA property we compute the Hausman tests defined in condition (3.9) using the set of odd-ratios in Tables 3.1 and 3.2. To compute this test we estimate seven restricted MNL models for both agricultural years in which each alternative is removed from the full model in turn. Table 3.3 shows the Chi-2 values for the Hausman test using the 21 common coefficients in each selection equation, $\hat{\gamma}_{jk}^{f}$ and $\hat{\gamma}_{jk}^{r}$. For example, if we remove beverage crops from the full model and compare the common coefficients in the profit equation of beef cattle, the Hausman test encounters systematic differences (Chi-2=308.67) therefore, the IIA does not hold. In contrast, the IIA assumption holds if poultry activities are excluded from the profit equation of beverage crops (Chi-2=28.92). The set of Hausman tests show that the IIA property does not hold in almost all cases in both samples.[126] The tests using the 31 alternatives adds further support to these findings. To confirm the invalidity of the IIA property and to investigate its implications, we estimate a set of NLs to obtain the corresponding dissimilarity parameters of arable and pastoral activities. By doing this, we are able to identify correlation patterns between particular sets of agricultural commodities.

**Table 3.3 Hausman tests (restricted models)**

| | Exclusion (2012) | | | | | | |
|---|---|---|---|---|---|---|---|
| **Equation** | **Beverage** | **Cattle** | **Fruits** | **Other** | **Pigs** | **Poultry** | **Vegetables** |
| **Beverage** | - | 408.70*** | 365.59*** | 392.73*** | 31.91* | 28.92 | 148.87*** |
| **Cattle** | 308.67*** | - | 784.81*** | 1103.22*** | 37.76** | 32.76* | 208.40*** |
| **Fruits** | 279.51*** | 518.36*** | - | 779.41*** | 43.06*** | 29.77 | 144.63*** |
| **Other** | 253.39*** | 242.03*** | 555.49*** | - | 77.14*** | 53.03*** | 217.03*** |
| **Pigs** | 46.13*** | 80.65*** | 66.70*** | 125.35*** | - | 13.32 | 69.35*** |
| **Poultry** | 47.55*** | 111.77*** | 77.73*** | 160.32*** | 27.29 | - | 41.43*** |
| **Vegetables** | 70.18*** | 158.22*** | 237.31*** | 236.24*** | 28.44 | 27.55 | - |
| | **Exclusion (2014)** | | | | | | |
| **Equation** | **Beverage** | **Cattle** | **Fruits** | **Other** | **Pigs** | **Poultry** | **Vegetables** |
| **Beverage** | - | 277.45*** | 398.91*** | 394.82*** | 37.29** | 28.23 | 166.57*** |
| **Cattle** | 234.42*** | - | 884.52*** | 647.63*** | 60.70*** | 35.95** | 161.71*** |
| **Fruits** | 210.26*** | 261.82*** | - | 491.02*** | 73.71*** | 27.67 | 92.30*** |
| **Other** | 134.78*** | 262.30*** | 533.13*** | - | 90.67*** | 30.88* | 126.40*** |
| **Pigs** | 59.21*** | 68.45*** | 161.99*** | 122.82*** | - | 20.87 | 54.13*** |
| **Poultry** | 123.93*** | 81.17*** | 54.01*** | 83.58*** | 37.52** | - | 29.63 |
| **Vegetables** | 99.04*** | 136.52*** | 140.86*** | 197.56*** | 43.05*** | 22.16 | - |

Note: Hausman tests estimated via the suest command in Stata 15.0 (clusters at the farm level)
Null hypothesis: difference in coefficients not systematic
*** p<0.01, ** p<0.05, * p<0.1
Chi2(d.f.): 22

[126] These results also hold using cross-prices in the choice equations. See Table 3.26 in Appendix 3A.2.

### *3.4.2. Nested Logit model*

The size of the data sets, the number of alternatives, and the complexity of the NL model prevent us to use the FIML estimator to fit the models depicted in Figures 3.4 and 3.6.[127] Therefore, we use the LIML method. In the first stage, we estimate a MNL for each branch. Using the estimated parameters, we compute the inclusive values using equation (3.10) for each branch. Then, in the second stage, we fit a Conditional Logit (CL) model for the top-level equation in which these inclusive values enter as *alternative-specific* variables. As this model uses plot-level data and a two-stage estimation, the standard errors of the coefficients in the top-level equation are consistent but not efficient and must be adjusted. To overcome this issue, we use the bootstrap method with 1,000 replications[128] to adjust standard errors of the $\lambda_h$ parameters as suggested in Cameron and Trivedi, 2005, pp. 510. For the bottom equations, we use the robust specification clustering the data at the farm level.

Tables 3.4 and 3.5 show the results using the nest design depicted in Figure 3.4. Odd-ratios in Tables 3.4 and 3.5 are not directly comparable to those in Tables 3.1 and 3.2 as cereals and pigs are defined as the base categories of the crops and livestock branches respectively. The results from the NL model confirms a nonlinear effect of climate on agriculturalists' decisions. The nonlinear interaction effect corroborates that more rainfall alleviates harmful effects from heat stress. Not all output prices and wage rate parameters are in line with theoretical underpinnings as in the MNL. The NL confirms that beef cattle production is mainly developed using (land) extensive practices rather than stabled livestock. Older farmers tend to select beverage crops and fruits, while farmers who recognise themselves as indigenous are reluctant

[127] After several attempts using a High-Performance Computing service (BlueBear at the University of Birmingham) the FIML method did not converge using different functional forms, nest structures, and both data sets.
[128] This algorithm draws a random sample of size $\tilde{n}$ from the full sample with replacement, then it estimates $\hat{\lambda}_h^*$ based on the corresponding subsample. These two steps are repeated $B$ times in order to obtain $\hat{\lambda}_{h1}^*, \dots, \hat{\lambda}_{hB}^*$. Thus, the bootstrap estimate of the variance-covariance matrix of $\hat{\lambda}_h^*$ is equal to: $\widehat{Var}(\hat{\lambda}) = \left(\frac{1}{B-1}\right)\sum_{b=1}^{B}(\hat{\lambda}_b^* - \hat{\lambda}^*)(\hat{\lambda}_b^* - \hat{\lambda}^*)'$ where $\hat{\lambda}^* = B^{-1}\sum_{b=1}^{B}\hat{\lambda}_b^*$ and the corresponding standard error of the $j$-th estimator of $\lambda$ is: $se(\hat{\lambda}_j) = \sqrt{\widehat{Var}_{j,j}(\hat{\lambda})}$.

to move away from the corresponding base category. The more educated the farmer is, the more likely to choose beverage crops, fruits, and other crops. The possession of a mobile phone and access to the internet boosts the probability of choosing fruits, other crops, and vegetables. Consistently, beef cattle production usually takes place in distant lands that are the same time not well connected. Overall, the results of the NL and the MNL coincide in terms of signs of odd-ratios but, the size of coefficients in Tables 3.4 and 3.5 need to be rescaled by the corresponding $\lambda_h$ as suggested by Heiss et al. (2002) and Hensher and Greene (2002).

Before we examine the correlation between individual commodities, let us assume that arable and non-arable alternatives are equally correlated. The second column in Tables 3.4 and 3.5 displays the results for the top choice equation depicted in Figure 3.4 in which we impose equality of dissimilarity parameters associated to crop and livestock activities. Both dissimilarity parameters range within the unit interval. This result indicates that the error terms in the MNL are not independent therefore, the IIA property does not hold. To investigate further the degree of correlation among individual commodities we relax the previous constraint in the NL for the 31 alternatives (see Tables 3.19-3.24 in Appendix A3.2). Adding further support to the invalidity of the IIA property, the set of dissimilarity parameters in both agricultural years ranges within the unit interval and individual values are different from one (see columns 4 and 5 in Table 3.6). This finding implies that error terms of alternatives within the same branch, e.g. cereals or fruits, are highly (close to zero) or moderately (close to 0.50) correlated. In other words, the probability for maize, rise, sorghum, barley, oat, and wheat rises by the same proportion when we remove any of the alternatives within the same group. This also applies for the remaining groups of alternatives.

## Table 3.4 Nested Logit model 8 alternatives (2012)

| VARIABLES | top choice | beverage | cereals | fruits | other | vegetables | cattle | pigs | poultry |
|---|---|---|---|---|---|---|---|---|---|
| **Inclusive values** | | | | | | | | | |
| Inclusive value | 0.5691*** | | | | | | | | |
| crops=livestock | (0.0116) | | | | | | | | |
| | [0.0113] | | | | | | | | |
| **Climate** | | | | | | | | | |
| Temperature | | 3.3556*** | | -0.6056*** | 0.9121*** | 0.9887*** | 0.7957** | | 3.0708*** |
| | | (0.1620) | | (0.0473) | (0.0687) | (0.3234) | (0.3670) | | (0.6235) |
| Temperature sq. | | -0.0786*** | | 0.0187*** | -0.0302*** | -0.0236*** | -0.0242*** | | -0.0769*** |
| | | (0.0039) | | (0.0011) | (0.0022) | (0.0089) | (0.0079) | | (0.0146) |
| Rainfall | | 0.7439*** | | 0.6729*** | -1.0273*** | -0.9958*** | -0.2985 | | -0.5568* |
| | | (0.0490) | | (0.0426) | (0.0583) | (0.1443) | (0.2440) | | (0.3305) |
| Rainfall sq. | | -0.0166*** | | -0.0137*** | -0.0083*** | 0.0040** | -0.0132*** | | -0.0026 |
| | | (0.0006) | | (0.0009) | (0.0008) | (0.0018) | (0.0037) | | (0.0043) |
| Temp.*Rainfall | | 0.0050** | | -0.0045** | 0.0563*** | 0.0320*** | 0.0350*** | | 0.0260* |
| | | (0.0022) | | (0.0018) | (0.0031) | (0.0074) | (0.0101) | | (0.0152) |
| Temperature SD | | -0.0816*** | | 0.0312*** | 0.0288*** | -0.0233*** | 0.0298** | | -0.0328* |
| | | (0.0054) | | (0.0031) | (0.0016) | (0.0069) | (0.0127) | | (0.0169) |
| Rainfall seasonality | | -0.0207*** | | -0.0027 | -0.0016 | -0.0003 | -0.0070 | | -0.0186** |
| | | (0.0025) | | (0.0021) | (0.0016) | (0.0025) | (0.0066) | | (0.0091) |
| **Output prices** | | | | | | | | | |
| Price beverage | | -0.0024** | | | | | | | |
| | | (0.0012) | | | | | | | |
| Price fruits | | | | 0.0209*** | | | | | |
| | | | | (0.0021) | | | | | |
| Price other | | | | | 0.0275*** | | | | |
| | | | | | (0.0020) | | | | |
| Price vegetables | | | | | | 0.0091*** | | | |
| | | | | | | (0.0027) | | | |
| Price cattle | | | | | | | 0.0003 | | |
| | | | | | | | (0.0083) | | |
| Price poultry | | | | | | | | | 0.0108 |
| | | | | | | | | | (0.0067) |
| **Inputs** | | | | | | | | | |
| Wage rate | | 0.0011 | | 0.0076*** | -0.0009 | 0.0094*** | -0.0063** | | -0.0032 |
| | | (0.0014) | | (0.0008) | (0.0007) | (0.0018) | (0.0031) | | (0.0038) |
| Plot size | | -0.1240*** | | 0.0367** | -0.0051 | -0.1240*** | 0.3246*** | | 0.0675 |
| | | (0.0251) | | (0.0182) | (0.0109) | (0.0296) | (0.0299) | | (0.0431) |
| **Socio-demographic characteristics** | | | | | | | | | |
| Age | | 0.0149*** | | 0.0153*** | 0.0023 | -0.0153*** | 0.0004 | | -0.0291*** |
| | | (0.0026) | | (0.0024) | (0.0019) | (0.0032) | (0.0087) | | (0.0111) |
| Indigenous | | -1.0696*** | | -0.8586*** | -1.3243*** | -1.4480*** | -0.4259 | | -2.6825** |
| | | (0.0877) | | (0.0799) | (0.0661) | (0.1968) | (0.3839) | | (1.0942) |
| Schooling | | 0.0322*** | | 0.0497*** | 0.0323*** | -0.0130 | -0.1096*** | | 0.0019 |
| | | (0.0088) | | (0.0080) | (0.0047) | (0.0115) | (0.0223) | | (0.0364) |
| **Access to markets** | | | | | | | | | |
| Mobile | | 0.0358 | | 0.4828*** | 0.0958** | 0.0451 | -0.3080 | | 0.4150 |
| | | (0.1473) | | (0.0603) | (0.0423) | (0.0913) | (0.2153) | | (0.3667) |
| Internet | | -0.2237 | | 0.2127 | 0.0727 | 0.5822*** | -2.0054*** | | -0.6132* |
| | | (0.2556) | | (0.1341) | (0.1177) | (0.1414) | (0.2208) | | (0.3260) |
| City | | -0.0587*** | | -0.0400*** | -0.0182*** | 0.0198** | 0.0351** | | -0.0205 |
| | | (0.0064) | | (0.0039) | (0.0023) | (0.0081) | (0.0143) | | (0.0219) |
| Road density | | 1.4170*** | | -1.8714*** | -1.0869*** | -0.2766 | -0.5500 | | 0.8113 |
| | | (0.1585) | | (0.1410) | (0.0855) | (0.2519) | (0.5084) | | (0.5856) |
| **Soils** | | | | | | | | | |
| Vertisol | | -0.0218*** | | -0.0041*** | -0.0044*** | -0.0044*** | 0.0060** | | 0.0070* |
| | | (0.0021) | | (0.0009) | (0.0006) | (0.0013) | (0.0030) | | (0.0037) |
| Feozem | | -0.0135*** | | 0.0069*** | -0.0020*** | -0.0007 | 0.0028 | | 0.0100*** |
| | | (0.0018) | | (0.0009) | (0.0005) | (0.0013) | (0.0028) | | (0.0033) |
| Regosol | | -0.0080*** | | -0.0012 | -0.0024** | 0.0081*** | 0.0134*** | | -0.0014 |
| | | (0.0012) | | (0.0013) | (0.0010) | (0.0017) | (0.0036) | | (0.0046) |
| Cambisol | | -0.0094*** | | -0.0078*** | -0.0078*** | -0.0002 | 0.0150*** | | 0.0151** |
| | | (0.0011) | | (0.0012) | (0.0009) | (0.0020) | (0.0049) | | (0.0071) |
| Constant | -4.3371*** | -41.8872*** | | -6.2915*** | -11.3305*** | -11.3442*** | -2.8583 | | -27.2084*** |
| | (0.0709) | (1.7440) | | (0.6086) | (0.5004) | (2.9173) | (4.6466) | | (7.2846) |
| | [0.0687] | | | | | | | | |
| Observations | 439,970 | 894,485 | | 894,485 | 894,485 | 894,485 | 123,264 | | 123,264 |

Top-level: robust standard errors in parentheses (clusters at the farm level)
Top-level: robust standard errors in brackets [using bootstrap and clusters at the farm level, 1000 replications]
Bottom-level: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

# Table 3.5 Nested Logit model 8 alternatives (2014)

| VARIABLES | top choice | beverage | cereals | fruits | other | vegetables | cattle | pigs | poultry |
|---|---|---|---|---|---|---|---|---|---|
| **Inclusive values** | | | | | | | | | |
| Inclusive value | 0.4595*** | | | | | | | | |
| crops=livestock | (0.0124) | | | | | | | | |
| | [0.0125] | | | | | | | | |
| **Climate** | | | | | | | | | |
| Temperature | | 3.4226*** | | -0.7741*** | 0.5175*** | 0.5483** | 0.3193 | | 0.6821 |
| | | (0.1574) | | (0.0503) | (0.0972) | (0.2697) | (0.4184) | | (0.7094) |
| Temperature sq. | | -0.0805*** | | 0.0211*** | -0.0219*** | -0.0127 | -0.0151* | | -0.0215 |
| | | (0.0038) | | (0.0012) | (0.0030) | (0.0078) | (0.0091) | | (0.0163) |
| Rainfall | | 0.7702*** | | 0.4602*** | -1.4475*** | -0.7397*** | -0.8236*** | | -0.5851* |
| | | (0.0648) | | (0.0507) | (0.0839) | (0.1642) | (0.3070) | | (0.3467) |
| Rainfall sq. | | -0.0166*** | | -0.0153*** | -0.0040*** | 0.0056** | -0.0066 | | -0.0040 |
| | | (0.0007) | | (0.0012) | (0.0010) | (0.0023) | (0.0053) | | (0.0065) |
| Temp.*Rainfall | | 0.0037 | | 0.0043** | 0.0677*** | 0.0192** | 0.0518*** | | 0.0375** |
| | | (0.0024) | | (0.0019) | (0.0043) | (0.0086) | (0.0128) | | (0.0151) |
| Temperature SD | | -0.0854*** | | 0.0466*** | 0.0182*** | -0.0487*** | 0.0458*** | | 0.0392 |
| | | (0.0054) | | (0.0027) | (0.0027) | (0.0095) | (0.0117) | | (0.0246) |
| Rainfall seasonality | | -0.0074*** | | -0.0143*** | 0.0035** | 0.0135*** | -0.0150** | | -0.0015 |
| | | (0.0026) | | (0.0019) | (0.0017) | (0.0032) | (0.0062) | | (0.0103) |
| **Output prices** | | | | | | | | | |
| Price beverage | | 0.0040** | | | | | | | |
| | | (0.0016) | | | | | | | |
| Price fruits | | | | 0.0173*** | | | | | |
| | | | | (0.0014) | | | | | |
| Price other | | | | | 0.0178*** | | | | |
| | | | | | (0.0033) | | | | |
| Price vegetables | | | | | | 0.0005 | | | |
| | | | | | | (0.0038) | | | |
| Price cattle | | | | | | | -0.0167*** | | |
| | | | | | | | (0.0056) | | |
| Price poultry | | | | | | | | | 0.0082 |
| | | | | | | | | | (0.0118) |
| **Inputs** | | | | | | | | | |
| Wage rate | | -0.0109*** | | -0.0013 | 0.0020* | 0.0064* | 0.0043 | | -0.0132 |
| | | (0.0026) | | (0.0013) | (0.0011) | (0.0034) | (0.0069) | | (0.0084) |
| Plot size | | -0.0891*** | | -0.0472** | -0.0083 | -0.0674** | 0.1929*** | | 0.0132 |
| | | (0.0213) | | (0.0197) | (0.0104) | (0.0314) | (0.0246) | | (0.0336) |
| **Socio-demographic characteristics** | | | | | | | | | |
| Age | | 0.0177*** | | 0.0191*** | 0.0015 | -0.0135*** | 0.0003 | | 0.0047 |
| | | (0.0024) | | (0.0023) | (0.0014) | (0.0038) | (0.0059) | | (0.0134) |
| Indigenous | | -0.6782*** | | 0.0165 | -0.1036* | -0.1926 | -0.7258*** | | -0.2262 |
| | | (0.0798) | | (0.0582) | (0.0530) | (0.1336) | (0.2146) | | (0.3871) |
| Schooling | | 0.0485*** | | 0.0496*** | 0.0146** | -0.0047 | 0.0116 | | -0.0034 |
| | | (0.0086) | | (0.0074) | (0.0070) | (0.0140) | (0.0228) | | (0.0379) |
| **Access to markets** | | | | | | | | | |
| Mobile | | -0.2619*** | | 0.2525*** | 0.3576*** | 0.1761 | -0.3299* | | -0.9410*** |
| | | (0.0983) | | (0.0607) | (0.0395) | (0.1588) | (0.1898) | | (0.3070) |
| Internet | | -0.0227 | | 0.4104*** | 0.2046* | 1.0280*** | -2.1411*** | | -0.0131 |
| | | (0.2300) | | (0.1172) | (0.1146) | (0.1456) | (0.2348) | | (0.4749) |
| City | | -0.0629*** | | -0.0530*** | -0.0103*** | 0.0278*** | 0.0661*** | | 0.0339 |
| | | (0.0053) | | (0.0040) | (0.0022) | (0.0096) | (0.0171) | | (0.0274) |
| Road density | | 1.9065*** | | -1.0634*** | -1.1674*** | -0.4146 | -0.0035 | | 1.8143** |
| | | (0.1220) | | (0.1286) | (0.1064) | (0.2957) | (0.4731) | | (0.7954) |
| **Soils** | | | | | | | | | |
| Vertisol | | -0.0186*** | | -0.0026*** | -0.0032*** | -0.0032** | 0.0053** | | -0.0061 |
| | | (0.0014) | | (0.0009) | (0.0008) | (0.0016) | (0.0023) | | (0.0039) |
| Feozem | | -0.0130*** | | 0.0057*** | -0.0011 | 0.0032* | 0.0047** | | -0.0048 |
| | | (0.0016) | | (0.0009) | (0.0007) | (0.0017) | (0.0022) | | (0.0047) |
| Regosol | | -0.0076*** | | 0.0015 | 0.0012 | 0.0143*** | 0.0162*** | | 0.0054 |
| | | (0.0011) | | (0.0012) | (0.0012) | (0.0020) | (0.0036) | | (0.0051) |
| Cambisol | | -0.0021** | | -0.0042*** | -0.0057*** | 0.0008 | 0.0208*** | | 0.0196** |
| | | (0.0010) | | (0.0013) | (0.0012) | (0.0022) | (0.0045) | | (0.0079) |
| Constant | -3.7310*** | -44.7345*** | | -2.6734*** | -5.5345*** | -7.2782*** | 3.1455 | | -9.2929 |
| | (0.0632) | (1.8492) | | (0.6697) | (0.5037) | (2.3594) | (5.5507) | | (9.1908) |
| | [0.0636] | | | | | | | | |
| Observations | 336,530 | 737,240 | | 737,240 | 737,240 | 737,240 | 62,451 | | 62,451 |

Top-level: robust standard errors in parentheses (clusters at the farm level)
Top-level: robust standard errors in brackets [using bootstrap and clusters at the farm level, 1000 replications]
Bottom-level: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

Previous studies argue that cross prices are also arguments of the profit functions. To investigate how the exclusion of those prices modify the correlation patterns, we estimate the NLs using prices of other alternatives and the corresponding inclusive values. Table 3.6 summarises the results for the 32 dissimilarity parameters (see Figures 3.4 and 3.6 for the nests designs). It is evident that IIA does not hold in all cases and interesting results emerge. First, aggregating the full set of alternatives into eight more general categories hides correlation patterns within branches at lower levels. Commodities within the two branches at the top level show moderate correlation. Second, by allowing the farmer to choose among the full set of alternatives, we identify different degrees of independence. For instance, individual products within the cereals, fruits, other crops, and vegetables groups are highly correlated while beverage crops and livestock activities show a moderate correlation. Third, the exclusion of cross prices from the individual profit functions increases the value of $\lambda_h$ in most of the cases. Consequently, aggregation of alternatives and the exclusion of cross prices from the choice equations hide and reduce the degree of correlation between unobserved factors within limbs respectively.

Ignoring the correlation patterns between similar alternatives by assuming IIA may have serious implications on simulations of the influence of climate change on farmers' production decisions. First, the set of parameters in Table 3.6 indicates that if the inclusive value for a particular group of alternatives rises, that group is preferred, and other categories are chosen less. Second, the closer to zero a dissimilarity parameter is, the higher the degree of correlation between alternatives within each group. According to our results pastoral and arable activities observe a moderate correlation (0.57 and 0.46), which has been ignored in previous studies as these investigations explore transitions between particular commodities within these two categories but not across them.

**Table 3.6 Dissimilarity parameters**

| | All prices | | Own-prices | |
|---|---|---|---|---|
| **Lambda** | **2012** | **2014** | **2012** | **2014** |
| | | **8 alternatives** | | |
| **Crops=Livestock** | 0.5393*** | 0.4238*** | 0.5691*** | 0.4595*** |
| | (0.0113) | (0.0120) | (0.0116) | (0.0124) |
| | [0.0110] | [0.0120] | [0.0113] | [0.0125] |
| | | **31 alternatives** | | |
| **Beverage crops** | 0.5790*** | 0.1581*** | 0.5843*** | 0.1961*** |
| | (0.0129) | (0.0054) | (0.0126) | (0.0065) |
| | [0.0129] | [0.0053] | [0.0126] | [0.0065] |
| **Cereals** | 0.0276*** | 0.0513*** | 0.0262*** | 0.0399*** |
| | (0.0020) | (0.0038) | (0.0018) | (0.0035) |
| | [0.0020] | [0.0039] | [0.0019] | [0.0035] |
| **Fruits** | 0.0944*** | 0.0433*** | 0.0779*** | 0.0517*** |
| | (0.0028) | (0.0020) | (0.0021) | (0.0017) |
| | [0.0027] | [0.0021] | [0.0021] | [0.0018] |
| **Livestock** | 0.5378*** | 0.4220*** | 0.5653*** | 0.4582*** |
| | (0.0108) | (0.0111) | (0.0112) | (0.0113) |
| | [0.0105] | [0.0110] | [0.0108] | [0.0113] |
| **Other crops** | 0.0273*** | 0.0309*** | 0.0177* | 0.0610*** |
| | (0.0095) | (0.0101) | (0.0094) | (0.0134) |
| | [0.0093] | [0.0100] | [0.0092] | [0.0134] |
| **Vegetables** | 0.1237*** | -0.0531 | 0.1769*** | -0.0940 |
| | (0.0343) | (0.0877) | (0.0404) | (0.0892) |
| | [0.0343] | [0.0863] | [0.0407] | [0.0882] |

Top-level: robust standard errors in parentheses (clusters at the farm level)
Top-level: robust standard errors in brackets [using bootstrap and clusters at the farm level, 1000 replications]
Bottom-level: robust standard errors in parentheses (clustering at the farm level)
Alternative Specific Constants at the top level
*** p<0.01, ** p<0.05, * p<0.1

The observed heterogeneity in the size of dissimilarity parameters reflects that the existence of a particular (new) alternative influences differently the probability of choosing any other alternative. For instance, commodities within the cereals category are highly correlated because the ownership of threshing machines, ploughs, mowers, and other equipment needed for maize production also allows the farmer to produce wheat, sorghum, barley and oat but this form of capital is not suitable for other activities such as fruits or livestock activities. Similarly, the ownership of stockyards, stables, feed or pasture storages, or sheds, facilitates the production of livestock but these facilities may not be required in other production processes. The moderate degree of correlation within the livestock group can be explained by the fact that beef cattle or dairy production may require a different type of facilities than the production of pigs and poultry, and not exactly the same machinery as in the example of cereals. Other factors such as specialisation of workers, the size of plots, and climate, may also determine the degree of correlation between alternatives.

To simulate the effect of climate change on crop and livestock choices, coefficients of the bottom level equations need to be rescaled by the corresponding dissimilarity parameter. In the following section, we consider these correlation patterns and compare the predictions from the MNL and NL using different climate change scenarios.

### *3.4.3. Climate change scenarios*

To identify the effect of climate change on farmers' decisions, we combine information from the MNL and NL with the climate projections from three Global Climate Models (GCMs)[129]: the Community Climate System Model 4.0 (CCSM4.0), Model for Interdisciplinary Research In Climate 5 (MIROC5) and Meteorological Research Institute Coupled General Circulation Model 3 (MRI-CGCM3) models for the four Representative Concentration Pathways (RCPs) used in the Fifth Assessment IPCC report. Using the geographical location of the sampled fields, we assign the corresponding projections of average temperature and rainfall for the 2061-2080 period to each plot in both samples. As a result of this matching, temperature is expected to rise between 0.71ºC and 4.43ºC and changes in the amount of rainfall are projected to range between -41.97% and 25.61% with respect to the current levels. In average, the sampled plots are expected to face a warmer and drier future. Tables 3.7 and 3.8 display the current distribution (baseline) and the average predicted probabilities for the eight aggregated alternatives[130] using the current and future climate scenarios. For the MNL predictions, we use the set of coefficients in Tables 3.1 and 3.2, the current values of the explanatory variables, and replace the current climate with the predicted values for each RCP and GCM to compute the probability of choosing any alternative in each particular plot. Regarding the NL, we compute

[129] We select these Global Climate Models based on Hidalgo and Alfaro (2014) and data availability in the Worldclim database.
[130] See Tables 3.26 and 3.27 in Appendix 3A.2 for the 31-alternatives projections.

the predicted probabilities in two steps. First, using the corresponding dissimilarity parameters in Table 3.6 we rescale coefficients from the first stage (Tables 3.4 and 3.5), then we calculate the probabilities of choosing particular alternatives at the bottom level using current values of explanatory variables and replacing climate with the GCMs' predictions. Second, we calculate the probability of choosing any group of commodities at the top level using the coefficients of inclusive values and alternative specific constants. By replicating the same exercise for the four climate change scenarios and both samples, we can compare predictions from the MNL and NL models and identify the consequences of assuming IIA.

The predictions from the MNL and NL are different in most of the cases. The main results suggest that: i) these models predict the opposite effect of climate changes on the selection of cereals, which is the group of commodities with the highest degree of correlation and is the major agricultural commodity in Mexico; ii) although both models indicate that Mexican agriculturalists are likely to abandon beverage crops, beef cattle, other crops and poultry, and to move their production efforts towards fruits and pigs as a consequence of climate change, the extent of these movements does not coincide; and iii) the set of predictions shows the same patterns in both samples NAS-2012 and NAS-2014.

Looking at individual commodities, we find heterogeneous effects within subsets of alternatives (see Tables 3.26 and 3.27 in Appendix A3.2) and remarkable differences on the predictions from the NL and MNL models. Overall, the main results suggests that: i) the MNL and NL models predict opposite effects for some commodities such as chillies, coffee, or squash; ii) both approaches suggest that a warmer and drier future will lead to move away from alfalfa, beans, cacao, beef cattle, red tomato, and sugar cane to barley, pigs and potatoes however, the size of these transitions is not the same across time and between models; iii) the effect of climate change on the probability of choosing any of the remaining alternatives varies across samples and scenarios.

## Table 3.7 Predicted probabilities 2061-2080, NAS-2012 (% of total number of plots allocated to an agricultural commodity)

| | | Average | Average | RCP2.6 | | | | | | RCP4.5 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | probability | probability | CCSM4 | | MIROC5 | | MRI-CGCM3 | | CCSM4 | | MIROC5 | | MRI-CGCM3 | |
| **Choice** | **Baseline** | **MNL[+]** | **NL[++]** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** |
| **Beverage crops** | 1.51 | 1.51 | 2.30 | 0.04 | 0.21 | 0.01 | 0.09 | 0.05 | 0.25 | 0.002 | 0.03 | 0.001 | 0.02 | 0.01 | 0.08 |
| **Cattle** | 18.26 | 18.26 | 17.34 | 9.86 | 17.17 | 6.97 | 16.82 | 9.79 | 16.92 | 3.92 | 16.07 | 4.00 | 16.04 | 7.00 | 16.70 |
| **Cereals** | 54.03 | 54.03 | 42.46 | **64.79** | 46.95 | **62.92** | 45.73 | **67.06** | 48.69 | **62.22** | 45.63 | **58.29** | 43.57 | **64.30** | 46.90 |
| **Fruits** | 4.02 | 4.02 | 8.34 | **17.27** | **18.84** | **23.67** | **22.84** | **15.97** | **18.32** | **31.13** | **28.00** | **34.14** | **30.19** | **23.10** | **23.10** |
| **Other** | 19.53 | 19.53 | 22.27 | 6.61 | 11.53 | 5.23 | 9.48 | 5.75 | 10.30 | 1.82 | 5.35 | 2.68 | 5.43 | 4.45 | 8.22 |
| **Pigs** | 0.22 | 0.22 | 0.71 | **0.41** | **1.39** | **0.45** | **1.77** | **0.39** | **1.61** | **0.49** | **2.57** | **0.50** | **2.60** | **0.46** | **1.91** |
| **Poultry** | 0.20 | 0.20 | 0.62 | 0.01 | 0.12 | 0.01 | 0.08 | 0.01 | 0.15 | 0.001 | 0.04 | 0.001 | 0.03 | 0.003 | 0.07 |
| **Vegetables** | 2.24 | 2.24 | 5.94 | 0.99 | **3.80** | 0.75 | **3.19** | 0.97 | **3.76** | 0.42 | **2.30** | 0.38 | **2.11** | 0.68 | **3.03** |
| **Total** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| **Temperature (ºC)*** | | **20.48 ºC**** | | +1.29 [0.86-1.49] | | +1.66 [1.24-2.30] | | +1.29 [0.71-2.02] | | +2.12 [1.55-2.50] | | +2.37 [1.68-3.23] | | +1.77 [1.08-2.51] | |
| **Rainfall (%)*** | | **71.07 mm.**** | | -2.09 [-13.53-(+)6.51] | | -3.02 [-21.50-(+)11.02] | | -9.80 [-41.97-(+)15.16] | | -7.13 [-26.18-(+)6.99] | | -5.74 [-29.94-(+)23.24] | | -5.41 [-27.29-(+)24.07] | |

| | | Average | Average | RCP6.0 | | | | | | RCP8.5 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | probability | probability | CCSM4 | | MIROC5 | | MRI-CGCM3 | | CCSM4 | | MIROC5 | | MRI-CGCM3 | |
| **Choice** | **Baseline** | **MNL[+]** | **NL[++]** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** |
| **Beverage crops** | 1.51 | 1.51 | 2.30 | 0.002 | 0.03 | 0.001 | 0.02 | 0.01 | 0.08 | 0.00002 | 0.002 | 0.00001 | 0.003 | 0.0002 | 0.01 |
| **Cattle** | 18.26 | 18.26 | 17.34 | 3.59 | 15.93 | 3.69 | 15.82 | 6.62 | 16.58 | 0.85 | 12.36 | 1.08 | 13.93 | 2.61 | 15.08 |
| **Cereals** | 54.03 | 54.03 | 42.46 | **61.12** | 44.94 | **58.78** | 43.59 | **64.02** | 46.73 | **45.23** | 35.63 | **45.49** | 35.59 | **52.41** | 40.00 |
| **Fruits** | 4.02 | 4.02 | 8.34 | **32.73** | **29.12** | **34.03** | **29.73** | **24.86** | **24.28** | **53.12** | **43.40** | **51.96** | **42.64** | **42.37** | **36.45** |
| **Other** | 19.53 | 19.53 | 22.27 | 1.69 | 5.08 | 2.61 | 5.77 | 3.44 | 7.43 | 0.25 | 1.46 | 0.88 | 2.13 | 1.92 | 3.48 |
| **Pigs** | 0.22 | 0.22 | 0.71 | **0.50** | **2.72** | **0.48** | **2.82** | **0.46** | **2.03** | **0.48** | **6.31** | **0.48** | **4.75** | **0.49** | **3.59** |
| **Poultry** | 0.20 | 0.20 | 0.62 | 0.001 | 0.03 | 0.001 | 0.03 | 0.003 | 0.06 | 0.00003 | 0.01 | 0.00003 | 0.01 | 0.0002 | 0.01 |
| **Vegetables** | 2.24 | 2.24 | 5.94 | 0.38 | 2.15 | 0.41 | 2.21 | 0.58 | **2.80** | 0.09 | 0.83 | 0.11 | 0.97 | 0.20 | 1.38 |
| **Total** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| **Temperature (ºC)*** | | **20.48 ºC**** | | +2.20 [1.57-2.63] | | +2.29 [1.68-3.05] | | +1.82 [1.38-2.46] | | +3.42 [2.41-3.99] | | +3.41 [2.54-4.43] | | +2.95 [2.08-3.84] | |
| **Rainfall (%)*** | | **71.07 mm.**** | | -6.62 [-25.68-(+)4.80] | | -6.02 [-25.99-(+)15.69] | | -6.05 [-27.52-(+)11.75] | | -11.40 [-39.99-(+)10.04] | | -7.51 [-35.83-(+)20.49] | | -8.26 [-33.68-(+)25.61] | |

Average probabilities using data from 2012: Baseline is the current plots' distribution
Bold (red) numbers indicate that the corresponding alternative is more (less) likely to be chosen with respect to the baseline under the corresponding scenario.
*Average change in all sampled plots [minimum and maximum change in brackets]
** Current average temperature and rainfall
[+] By definition, the sample average predicted probabilities are equal to the observed sample frequencies when the MNL model includes the intercept. This property does not necessarily mean that this model performs better that other discrete choice models (Cameron and Trivedi, 2011, p. 501)
[++] The average predicted probabilities in the sample are no longer equal to the observed frequencies. This does not mean that the NL model fit is poor.

## Table 3.8 Predicted probabilities 2061-2080, NAS-2014 (% of total number of plots allocated to an agricultural commodity)

| Choice | Baseline | Average probability MNL+ | Average probability NL++ | RCP2.6 CCSM4 MNL | RCP2.6 CCSM4 NL | RCP2.6 MIROC5 MNL | RCP2.6 MIROC5 NL | RCP2.6 MRI-CGCM3 MNL | RCP2.6 MRI-CGCM3 NL | RCP4.5 CCSM4 MNL | RCP4.5 CCSM4 NL | RCP4.5 MIROC5 MNL | RCP4.5 MIROC5 NL | RCP4.5 MRI-CGCM3 MNL | RCP4.5 MRI-CGCM3 NL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Beverage crops** | 2.56 | 2.56 | 3.78 | 0.08 | 0.54 | 0.02 | 0.29 | 0.09 | 0.60 | 0.003 | 0.12 | 0.001 | 0.08 | 0.01 | 0.22 |
| **Cattle** | 11.88 | 11.88 | 10.09 | 4.80 | 9.91 | 2.93 | 9.71 | 4.35 | 9.63 | 1.52 | 9.30 | 1.45 | 9.49 | 2.79 | 9.66 |
| **Cereals** | 58.72 | 58.72 | 41.33 | **63.41** | 42.29 | 58.53 | 40.44 | **65.76** | 43.83 | 57.00 | 40.25 | 50.02 | 37.13 | **60.24** | 41.31 |
| **Fruits** | 5.16 | 5.16 | 11.64 | **21.08** | **22.87** | **29.78** | **28.04** | **19.88** | **22.57** | **37.12** | **33.19** | **43.03** | **36.55** | **28.48** | **27.83** |
| **Other** | 19.08 | 19.08 | 23.11 | 8.72 | 15.50 | 7.14 | 13.15 | 8.02 | 14.10 | 3.11 | 9.03 | 4.44 | 9.34 | 6.95 | 12.57 |
| **Pigs** | 0.38 | 0.38 | 1.30 | **0.39** | **1.70** | 0.35 | **1.98** | 0.36 | **1.99** | 0.32 | **2.43** | 0.28 | **2.32** | 0.34 | **2.04** |
| **Poultry** | 0.12 | 0.12 | 0.98 | 0.04 | **0.76** | 0.02 | **0.69** | 0.04 | **0.75** | 0.01 | **0.64** | 0.01 | **0.57** | 0.02 | **0.67** |
| **Vegetables** | 2.11 | 2.11 | 7.78 | 1.48 | **6.42** | 1.22 | **5.71** | 1.50 | **6.23** | 0.92 | **5.04** | 0.77 | **4.52** | 1.18 | **5.70** |
| **Total** | **100** | **100** | **100** | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| **Temperature (ºC)*** | | **20.67 ºC**** | | +1.28 [0.85-1.49] | | +1.69 [1.24-2.30] | | +1.31 [0.71-2.02] | | +2.11 [1.55-2.49] | | +2.41 [1.68-3.23] | | +1.77 [1.08-2.42] | |
| **Rainfall (%)*** | | **66.35 mm.**** | | -1.75 [-13.53-(+)6.51] | | -3.67 [-21.50-(+)10.95] | | -10.65 [-41.97-(+)15.16] | | -6.63 [-26.18-(+)6.99] | | -5.59 [-29.94-(+)23.50] | | -5.55 [-23.50-(+)24.07] | |

| Choice | Baseline | Average probability MNL+ | Average probability NL++ | RCP6.0 CCSM4 MNL | RCP6.0 CCSM4 NL | RCP6.0 MIROC5 MNL | RCP6.0 MIROC5 NL | RCP6.0 MRI-CGCM3 MNL | RCP6.0 MRI-CGCM3 NL | RCP8.5 CCSM4 MNL | RCP8.5 CCSM4 NL | RCP8.5 MIROC5 MNL | RCP8.5 MIROC5 NL | RCP8.5 MRI-CGCM3 MNL | RCP8.5 MRI-CGCM3 NL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Beverage crops** | 2.56 | 2.56 | 3.78 | 0.003 | 0.11 | 0.001 | 0.08 | 0.01 | 0.24 | 0.00001 | 0.01 | 0.00001 | 0.01 | 0.00013 | 0.03 |
| **Cattle** | 11.88 | 11.88 | 10.09 | 1.39 | 9.25 | 1.44 | 9.18 | 2.60 | 9.55 | 0.27 | 7.95 | 0.33 | 8.78 | 0.82 | 9.15 |
| **Cereals** | 58.72 | 58.72 | 41.33 | 55.38 | 39.57 | 51.73 | 3.75 | **59.82** | 41.28 | 34.96 | 30.69 | 34.80 | 29.44 | 42.91 | 34.08 |
| **Fruits** | 5.16 | 5.16 | 11.64 | **39.12** | **34.36** | **41.47** | **35.76** | **30.43** | **29.03** | **63.68** | **50.63** | **62.88** | **50.63** | **52.04** | **42.68** |
| **Other** | 19.08 | 19.08 | 23.11 | 2.95 | 8.75 | 4.21 | 9.35 | 5.69 | 11.58 | 0.62 | 3.55 | 1.48 | 4.74 | 3.54 | 7.27 |
| **Pigs** | 0.38 | 0.38 | 1.30 | 0.31 | **2.49** | 0.29 | **2.60** | 0.34 | **2.16** | 0.16 | **3.98** | 0.17 | **3.18** | 0.20 | **2.75** |
| **Poultry** | 0.12 | 0.12 | 0.98 | 0.01 | **0.63** | 0.01 | **0.59** | 0.02 | **0.67** | 0.001 | **0.44** | 0.002 | **0.42** | 0.005 | **0.48** |
| **Vegetables** | 2.11 | 2.11 | 7.78 | 0.85 | **4.84** | 0.85 | **4.68** | 1.09 | **5.51** | 0.31 | **2.74** | 0.34 | **2.81** | 0.48 | **3.57** |
| **Total** | **100** | **100** | **100** | 100 | 100 | 100 | 66 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| **Temperature (ºC)*** | | **20.67 ºC**** | | +2.19 [1.57-2.63] | | +2.32 [1.68-3.05] | | +1.83 [1.38-2.39] | | +3.40 [2.42-3.99] | | +3.46 [2.54-4.43] | | +2.96 [2.07-3.84] | |
| **Rainfall (%)*** | | **66.35 mm.**** | | -6.07 [-25.68-(+)4.80] | | -6.72 [-25.99-(+)15.88] | | -6.28 [-27.52-(+)11.75] | | -10.68 [-39.99-(+)10.04] | | -7.92 [-35.83-(+)21.34] | | -8.89 [-33.68-(+)25.61] | |

Average probabilities using data from 2014: Baseline is the current plots' distribution
Bold (red) numbers indicate that the corresponding alternative is more (less) likely to be chosen with respect to the baseline under the corresponding scenario.
*Average change in all sampled plots [minimum and maximum change in brackets]
**Current average temperature and rainfall
+ By definition, the sample average predicted probabilities are equal to the observed sample frequencies when the MNL model includes the intercept. This property does not necessarily mean that this model performs better that other discrete choice models (Cameron and Trivedi, 2011, p. 501)
++ The average predicted probabilities in the sample are no longer equal to the observed frequencies. This does not mean that the NL model fit is poor.

Some of the aforementioned transitions are in line with predictions in the existing literature in Africa and South America (Seo et al., 2008a; Seo and Mendelsohn, 2008) but as other studies use a limited number of alternatives, and in most of the cases different commodities, the comparison of these findings with previous investigations are not always possible. As these predictions are simultaneous effects of changes in temperature and rainfall on farmers' choices, these trends may reflect either a stronger influence from the former variable, from the latter, or a combination of both. For example, the abandonment of cacao, beef cattle, oranges, soy, and sugar cane and the preference for barley, potatoes, and sometimes wheat may be caused by water shortage. Conversely, warmer conditions probably make alfalfa and grapes less suitable for the sampled fields and bananas and sometimes lemons, melons, and squash more appropriate. Overall, these results indicate that the assumption of IIA matters, the MNL and NL lead to different predictions; and that aggregation of alternatives hides heterogeneous effects.

The predicted transitions from some cereals and beef cattle to the production of other agricultural commodities have important implications. The likely abandonment of maize and beans places additional challenges to food security, as these products are the staple food in many regions, especially in rural areas. Regarding land use, the most land extensive activity, beef cattle, is predicted to be less preferred which may reduce deforestation rates. In terms of Government policy, we find that PROCAMPO and PROGAN cash transfers prevent farmers to choose alternatives other than cereals and livestock, especially maize and beef cattle (see Table 3.12 in Appendix A3.2). This seems to be an obstacle for switching crops as an adaptive strategy.

## 3.5. Conclusions

Using cross-sectional data sets for two agricultural years, this paper analyses the influence of climate change on crops and livestock choices in Mexico. Unlike previous studies we take advantage of a new database to explore likely transitions between 31 crops and types of livestock within the same analysis, the quality of this data allows us to relax the IIA restriction by grouping together close substitutes and estimating a NL model, the high variability of farm gate prices at the municipality level improves the estimation results as we use *ex-ante* expected output prices rather than *ex-post* prices, and rather than analysing choices based only on the 'main' crop grown or the 'most prevalent' type of livestock raised or 'combination' of products per farm this investigation relies on observed choices at the plot-level.

The MNL and NL models confirm that Mexican agriculturalists are indeed sensitive to climate. There exists a nonlinear relationship between climate and the probability of choosing any of the alternatives, and the significance of the nonlinear interaction term suggests that choice models in previous studies ignore that more abundant rainfall mitigates harmful effects from heat stress. Aside of the effect of climate we find that possession of a mobile phone and access to the internet incline farmers to choose fruits, other crops, vegetables, and cattle, possibly to access information on the weather or current market conditions amongst other things. Being part of an indigenous community strongly inclines agriculturalists to choose maize, alfalfa, and oranges. Interesting findings also emerge with respect to the impact of government policies. Although PROCAMPO subsidy was not intended to alter farmers' production decisions our findings suggest that they strongly incentivizes the production of barley, beans, cotton, maize, sorghum, soy, and wheat. Recalling the initial eligibility criteria to enrol lands into the PROCAMPO programme, farmers had to plant any of the nine major crops in Mexico in 1994. The seven crops above are part of such list. Given that the government removed such restriction in 1995 (beneficiaries are permitted to cultivate any legal crop since 1995) and the fact that PROCAMPO still incentivises their production may indicate that recipients are not fully aware of the removal of such restriction or simply that they are unwilling to choose different crops due to cash transfers. Similarly, the PROGAN programme boosts the chances of choosing alfalfa, oat, and beef cattle over the remaining alternatives.

This paper also finds strong empirical evidence against the validity of the IIA assumption, which underpins the MNL model. The Hausman tests reveal the presence of systematic differences between common odd-ratios once we remove or add a particular commodity to the full set of alternatives. Adding further support to this finding, the set of dissimilarity parameters ranges within the unit interval which reveals that there exists a certain degree of correlation between error terms of the choice equations. From the set of dissimilarity parameters we find high correlation between alternatives within the cereals, fruits, other crops, and vegetables categories, and moderate correlation in the beverage crops and livestock groups. This correlation among alternatives can be attributable to the flexibility of different types of capital or of workers' skills or of intermediate inputs that are used in different production processes. The omission of these constraints in previous studies may have serious implications on the set of predictions about potential effects of climate change on farmers' decisions.

To investigate how the IIA assumption influences the abovementioned predictions we combine information from the MNL and NL models with the climate projections from three Global Climate Models. The main results suggest that predictions from these discrete choice models differ in almost all scenarios. These models predict the opposite effect of climate change on the probability of choosing cereals, which is the major crop in Mexico and observes the highest degree of correlation among particular commodities within this category. Although both models suggest transitions from beverage crops, beef cattle, and other crops to fruits and in some cases vegetables as a consequence of climate change, the extent of these movements differ between the NL and MNL models. These distortions have serious implications for the policy-making process, as it is likely that crops and types of livestock other than the 31 commodities in this study or less preferred alternatives may be suitable for different climatic conditions. Therefore, the use of the MNL model to analyse crop and livestock switching as strategies for adapting to climate change may lead to biased results, especially because the IIA seems unrealistic in this context.

To interpret the results in this paper the reader should take into account some caveats. First, the complexity of the NL model prevents us to use the FIML method, which is typically superior to the LIML estimator. Second, omitted variables may cause some bias in the set of coefficients. Third, the set of projections assumes that arguments of the profit functions other than climate remain unchanged. Changes on prices, technology, and access to information may alter these predictions. Fourth, the omission of carbon fertilisation may also lead to biased estimations as this causes changes in crop yields (Reilly et al., 2001). Further research should compare the current choices of farmers using high and low technology and explore differential consequences for crop and livestock choices. Furthermore, as it is likely to observe movements between different varieties of the same crop or between breeds of livestock as climatic conditions change, and such transitions should be preferred over those climate change adaptation strategies that require large investments on fixed capital, it is important to consider these processes in future studies.

## References


Allison, F.E., 1973. *Soil organic matter and its role in crop production* (Vol. 3). Elsevier.

Cameron, A. C. and Trivedi, P. K., 2005. *Microeconometrics: methods and applications.* Cambridge university press.

Cameron, A. C. and Trivedi, P. K., 2011. *Microeconometrics using Stata (revised edition).* Stata press.

Cheng, S. and Long, J.S., 2007. Testing for IIA in the multinomial logit model. *Sociological methods & research*, *35*(4), pp.583-600.

Domencich, T.A. and McFadden, D., 1975. *Urban travel demand-a behavioral analysis*. Technical report.

FAO, 2006. A system of integrated agricultural censuses and surveys: World Programme for the Census of Agriculture 2010, volume 1. *FAO Statistical development series*.

FAO, 2017. FAOSTAT. Rome, Italy. From http://www.fao.org/faostat/en/#data/OA. 12 July 2018.

FAO, ISSS, I., 1994. *World reference base for soil resources*. Technical report.

Fezzi, C. and Bateman, I., 2015. The impact of climate change on agriculture: Nonlinear effects and aggregation bias in Ricardian models of farmland values. *Journal of the Association of Environmental and Resource Economists*, *2*(1), pp.57-92.

Free, J.B., 1970. Insect pollination of crops. *Insect pollination of crops*.

Greene, W. H., 2000. *Econometric analysis (International edition).* Pearson US Imports & PHIPEs.

Hassan, R. and Nhemachena, C., 2008. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *African Journal of Agricultural and Resource Economics*, *2*(1), pp.83-104.

Hauber, A.B. and Parsons, G.R., 2000. The effect of nesting structure specification on welfare estimation in a random utility model of recreation demand: An application to the demand for recreational fishing. *American Journal of Agricultural Economics*, *82*(3), pp.501-514.

Hausman, J. and McFadden, D., 1984. Specification tests for the multinomial logit model. *Econometrica: Journal of the Econometric Society*, pp.1219-1240.

Hausman, J.A. and Wise, D.A., 1978. A conditional probit model for qualitative choice: Discrete decisions recognizing interdependence and heterogeneous preferences. *Econometrica: Journal of the econometric society*, pp.403-426.

Hausman, J.A., 1978. Specification tests in econometrics. *Econometrica: Journal of the econometric society*, pp.1251-1271.

Heiss, F., 2002. Structural choice analysis with nested logit models. *The Stata Journal*, *2*(3), pp.227-252.

Hensher, D.A. and Greene, W.H., 2002. Specification and estimation of the nested logit model: alternative normalisations. *Transportation Research Part B: Methodological*, *36*(1), pp.1-17.

Hensher, D.A., 1986. Sequential and full information maximum likelihood estimation of a nested logit model. *The Review of Economics and Statistics*, pp.657-667.

Herriges, J.A. and Kling, C.L., 1996. Testing the consistency of nested logit models with utility maximization. *Economics Letters*, *50*(1), pp.33-39.

Herriges, J.A. and Kling, C.L., 1997. The performance of nested logit models when welfare estimation is the goal. *American Journal of Agricultural Economics*, *79*(3), pp.792-802.

Hidalgo, H.G. and Alfaro, E.J., 2015. Skill of CMIP5 climate models in reproducing 20th century basic climate features in Central America. *International Journal of Climatology*, *35*(12), pp.3397-3421.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. and Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology*, *25*(15), pp.1965-1978.

Huang, J.C. and Zhao, M.Q., 2015. Model selection and misspecification in discrete choice welfare analysis. *Applied Economics*, *47*(39), pp.4153-4167.

IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. *IPCC*, Geneva, Switzerland, 151 pp.

Jones, L. and Boyd, E., 2011. Exploring social barriers to adaptation: insights from Western Nepal. *Global Environmental Change*, 21(4), pp.1262-1274.

Kling, C.L. and Herriges, J.A., 1995. An empirical investigation of the consistency of nested logit models with utility maximization. *American Journal of Agricultural Economics*, *77*(4), pp.875-884.

Kurukulasuriya, P. and Mendelsohn, R., 2008. Crop switching as a strategy for adapting to climate change. *African Journal of Agricultural and Resource Economics*, *2*(1), pp.105-126.

Lee, B., 1999. Calling patterns and usage of residential toll service under self selecting tariffs. *Journal of Regulatory economics*, *16*(1), pp.45-82.

McFadden, D., Talvitie, A., Cosslett, S., Hasan, I., Johnson, M., Reid, F. and Train, K., 1977a. Demand model estimation and validation. *Urban Travel Demand Forecasting Project, Phase*, *1*.

McFadden, D., Tye, W.B. and Train, K., 1977b. *An application of diagnostic tests for the independence from irrelevant alternatives property of the multinomial logit model* (pp. 39-45). Institute of Transportation Studies, University of California.

Mendelsohn, R. and Seo, S.N., 2007. *Climate change adaptation in Africa: a microeconomic analysis of livestock choice*. The World Bank.

Mendelsohn, R.O. and Dinar, A., 2009. *Climate change and agriculture: an economic analysis of global impacts, adaptation and distributional effects*. Edward Elgar Publishing.

Moniruzzaman, S., 2015. Crop choice as climate change adaptation: Evidence from Bangladesh. *Ecological Economics*, *118*, pp.90-98.

Ou, L. and Mendelsohn, R., 2017. An analysis of climate adaptation by livestock farmers in the Asian tropics. *Climate Change Economics*, *8*(03), p.1740001.

Perry, C., Steduto, P., Allen, R.G. and Burt, C.M., 2009. Increasing productivity in irrigated agriculture: Agronomic constraints and hydrological realities. *Agricultural water management,* 96(11), pp.1517-1524.

Reed, B., Mendelsohn, R. and Abidoye, B.O., 2017. The economics of crop adaptation to climate change in South-East Asia. *Climate Change Economics*, *8*(03), p.1740002.

Reilly, J., Tubiello, F., McCarl, B. and Melillo, J., 2001. Climate change and agriculture in the United States. *Climate Change Impacts on the United States: US National Assessment of the Potential Consequences of Climate Variability and Change: Foundation*, pp.379-403.

SAGARPA, 2018. PROCAMPO: antecedentes. Retrieved from: https://www.sagarpa.gob.mx/procampo/antecendentes

Schwiebert, J., 2015. Multinomial choice models based on Archimedean copulas. *AStA Advances in Statistical Analysis*, *100*(3), pp.333-354.

Seo, N., Mendelsohn, R., Dinar, A., Kurukulasuriya, P. and Hassan, R., 2008b. *Long-term adaptation: Selecting farm types across agro-ecological zones in Africa*. The World Bank.

Seo, N., Mendelsohn, R., Kurukulasuriya, P., Dinar, A. and Hassan, R., 2008a. *Differential adaptation strategies to climate change in African cropland by agro-ecological zones*. The World Bank.

Seo, S.N. and Mendelsohn, R., 2008. An analysis of crop choice: Adapting to climate change in South American farms. *Ecological economics*, *67*(1), pp.109-116.

Seo, S.N., McCarl, B.A. and Mendelsohn, R., 2010. From beef cattle to sheep under global warming? An analysis of adaptation by livestock species choice in South America. *Ecological Economics*, *69*(12), pp.2486-2494.

Small, K.A. and Brownstone, D., 1982. *Efficient estimation of nested logit models: an application to trip timing*. Princeton, USA: Princeton University.

Small, K.A., 1982. The scheduling of consumer activities: work trips. *The American Economic Review*, *72*(3), pp.467-479.

Thobani, M., 1984. A nested logit model of travel mode to work and auto ownership. *Journal of Urban Economics*, *15*(3), pp.287-301.

Train, K. E., 2009. *Discrete choice methods with simulation*. Cambridge university press.

Train, K.E., McFadden, D.L. and Ben-Akiva, M., 1987. The demand for local telephone service: A fully discrete model of residential calling patterns and service choices. *The RAND Journal of Economics*, pp.109-123.

Wang, J., Mendelsohn, R., Dinar, A. and Huang, J., 2008. *How China's farmers adapt to climate change*. The World Bank.

Zilberman, D., Liu, X., Roland-Holst, D. and Sunding, D., 2004. The economics of climate change in agriculture. *Mitigation and Adaptation Strategies for Global Change,* 9(4), pp.365-382.

# Appendix

## *A3.1. Temperature, rainfall and choices*

**Figure 3.7 Plot-level choices and climate (ranges)**

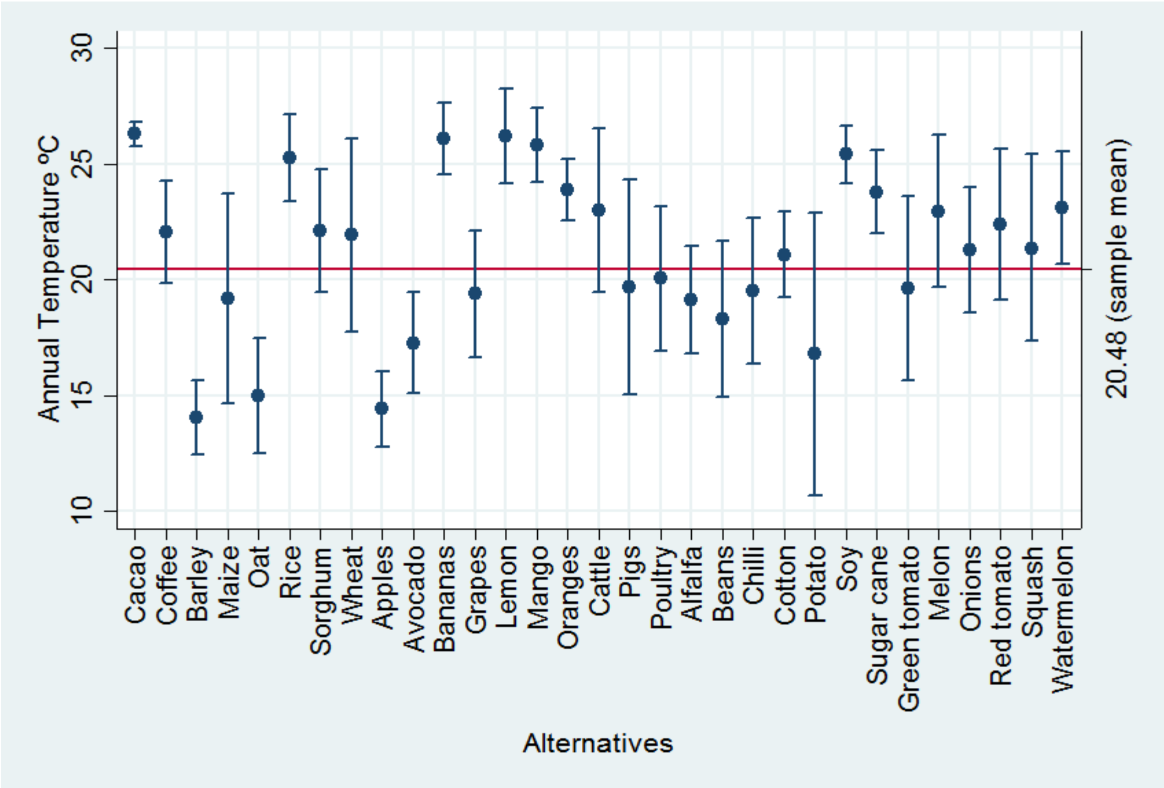



**Figure 3.7a. Temperature and choices NAS-2012**

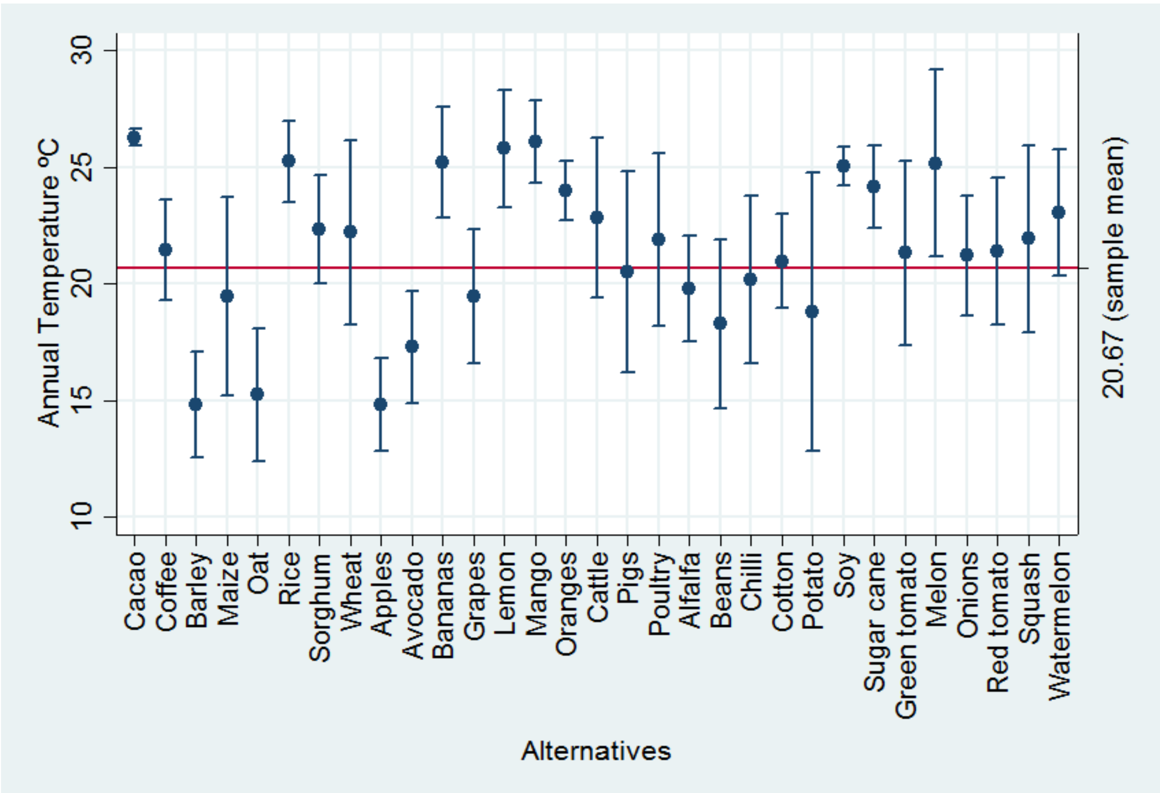



**Figure 3.7b Temperature and choices NAS-2014**

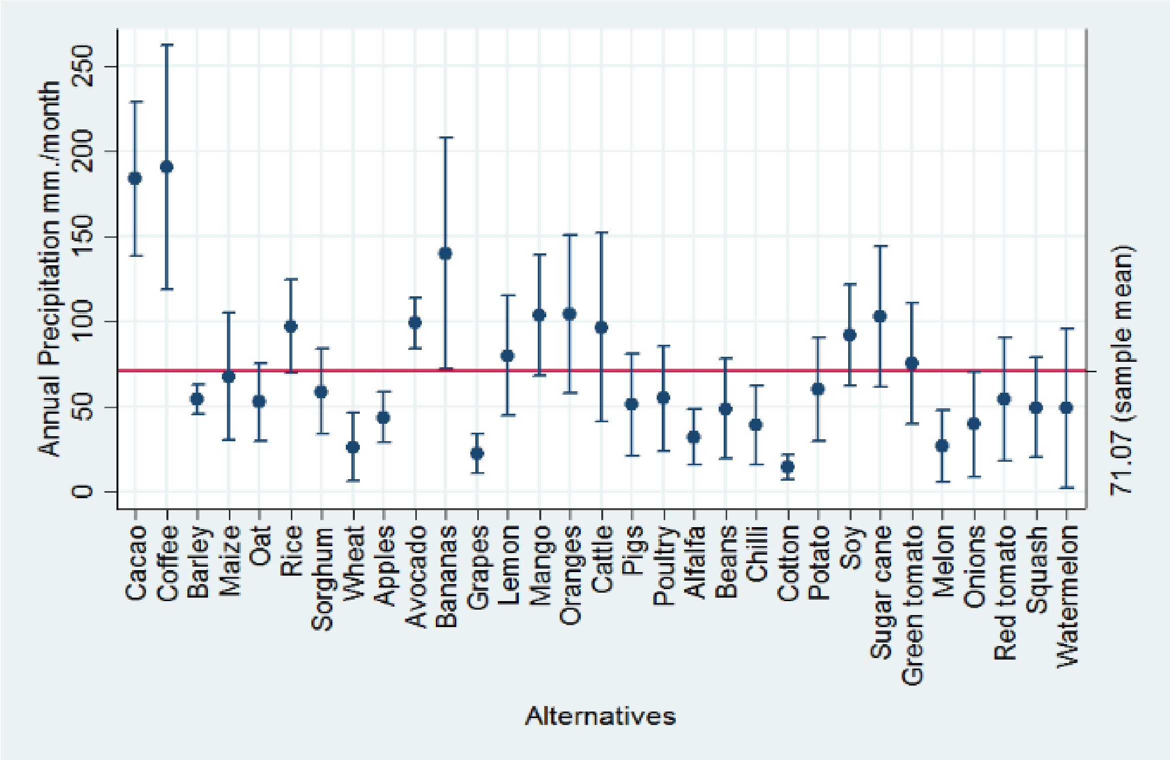



**Figure 3.7c Rainfall and choices NAS-2012**

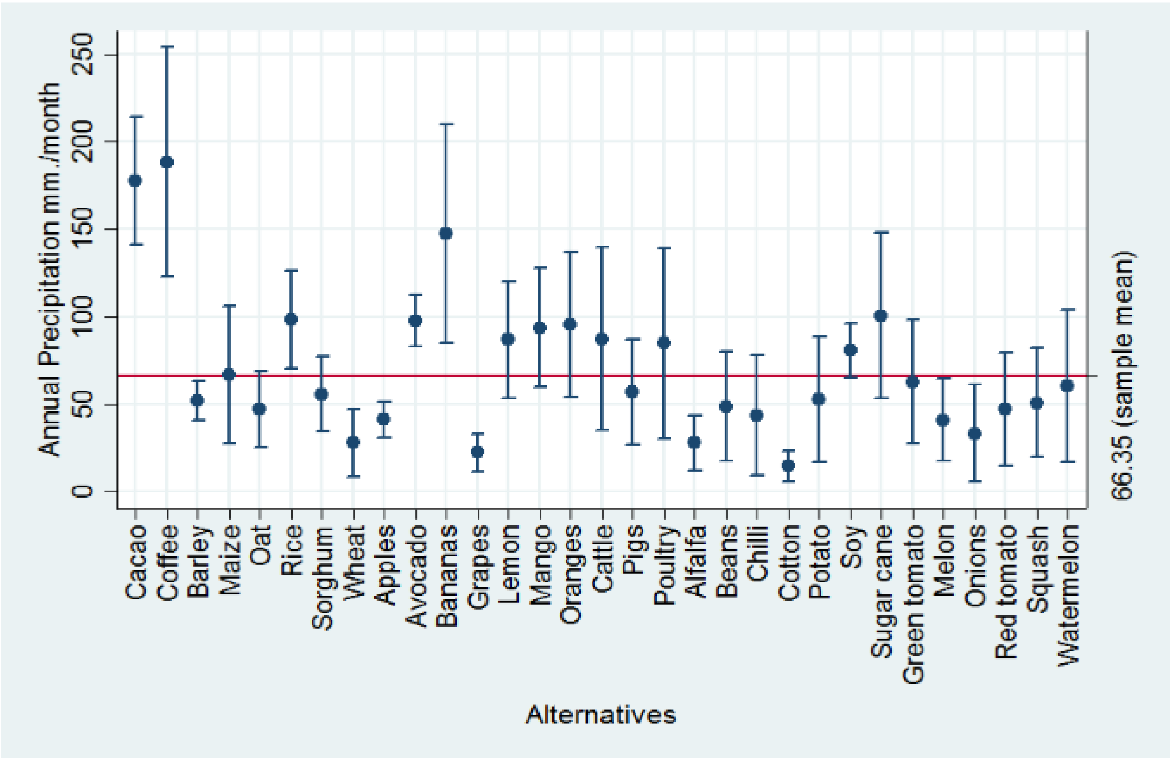



**Figure 3.7d Rainfall and choices NAS-2014**

## *A3.2. Summary statistics and additional estimations*

### Table 3.9 Definitions and summary statistics

| Variable | Definition | Units | Level | Mean | | S.D. | | Min. | | Max. | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 2012 | 2014 | 2012 | 2014 | 2012 | 2014 | 2012 | 2014 |
| **Dependent variable** | | | | | | | | | | | |
| Choice | Chosen alternative | Categorical | Plot | - | | - | | 1 | | 31 | |
| **Climate** | | | | | | | | | | | |
| Temperature | Average temperature 1950-2000 | Celsius | CA | 20.48 | 20.67 | 4.46 | 4.20 | 7.21 | 6.51 | 29.34 | 29.40 |
| Rainfall | Average rainfall 1950-2000 | mm/month | CA | 71.07 | 66.35 | 46.82 | 46.79 | 4.30 | 4.30 | 387.82 | 384.43 |
| Diurnal | Temperature range 1950-2000 | Celsius | CA | 15.19 | 15.22 | 2.43 | 2.47 | 7.94 | 7.97 | 20.32 | 20.50 |
| **Output prices** | | | | | | | | | | | |
| Price of beverage | Fisher index 07-11 and 09-13* | % | Mun. | 172 | 215 | 20 | 14 | 57 | 124 | 319 | 301 |
| Price of cattle | Fisher index 07-11 and 09-13* | % | Mun. | 109 | 117 | 14 | 17 | 64 | 76 | 169 | 174 |
| Price of cereals | Fisher index 07-11 and 09-13* | % | Mun. | 160 | 181 | 11 | 14 | 119 | 129 | 204 | 247 |
| Price of fruits | Fisher index 07-11 and 09-13* | % | Mun. | 135 | 154 | 11 | 17 | 102 | 97 | 180 | 211 |
| Price of other | Fisher index 07-11 and 09-13* | % | Mun. | 135 | 148 | 10 | 18 | 107 | 115 | 154 | 183 |
| Price of pigs | Fisher index 07-11 and 09-13* | % | Mun. | 114 | 126 | 15 | 21 | 54 | 53 | 177 | 201 |
| Price of poultry | Fisher index 07-11 and 09-13* | % | Mun. | 131 | 150 | 17 | 22 | 71 | 82 | 196 | 239 |
| Price of vegetables | Fisher index 07-11 and 09-13* | % | Mun. | 117 | 123 | 16 | 19 | 58 | 40 | 185 | 223 |
| **Inputs** | | | | | | | | | | | |
| Wage rate | Average wage rate | $/hour | Mun. | 36.49 | 29.08 | 24.63 | 19.64 | 6.25 | 3.08 | 293.35 | 124.19 |
| Plot size | Size of the plot | ha | Plot | 54.59 | 42.42 | 487.59 | 481.58 | 0.00 | 0.00 | 49,000 | 116,468 |
| **Socio-demographic characteristics** | | | | | | | | | | | |
| Age | Age of the farmer | years | Farm | 56.92 | 57.71 | 13.40 | 12.73 | 18.00 | 18.00 | 90.00 | 100.00 |
| Indigenous | 1= if indigenous, 0=otherwise | binary | Farm | 0.07 | 0.15 | 0.26 | 0.36 | 0.00 | 0.00 | 1.00 | 1.00 |
| Schooling | Years of study | years | Farm | 8.41 | 7.89 | 5.38 | 4.82 | 0.00 | 1.00 | 29.00 | 28.00 |
| **Access to markets** | | | | | | | | | | | |
| Mobile | 1=mobile phone, 0=otherwise | binary | Farm | 0.43 | 0.54 | 0.49 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 |
| Internet | 1=internet, 0=otherwise | binary | Farm | 0.13 | 0.19 | 0.34 | 0.39 | 0.00 | 0.00 | 1.00 | 1.00 |
| Near city | Distance to the nearest city | km | CA | 8.63 | 9.29 | 9.70 | 10.22 | 0.00 | 0.00 | 141.62 | 135.69 |
| Road density | Roads length/total area | km/km2 | Mun. | 0.34 | 0.31 | 0.28 | 0.25 | 0.00 | 0.01 | 2.62 | 2.06 |
| **Soils** | | | | | | | | | | | |
| Vertisol | Area of vertisol soils | % | CA | 21.45 | 22.49 | 38.44 | 39.14 | 0.00 | 0.00 | 100.00 | 100.00 |
| Feozem | Area of feozem soils | % | CA | 15.57 | 15.19 | 32.95 | 32.65 | 0.00 | 0.00 | 100.00 | 100.00 |
| Regosol | Area of regosol soils | % | CA | 12.09 | 11.19 | 29.37 | 28.27 | 0.00 | 0.00 | 100.00 | 100.00 |
| Cambisol | Area of cambisol soils | % | CA | 8.93 | 7.81 | 25.88 | 24.07 | 0.00 | 0.00 | 100.00 | 100.00 |
| **Subsidies** | | | | | | | | | | | |
| Procampo** | 1=procampo, 0=otherwise | binary | Farm | - | 0.56 | - | 0.50 | - | 0.00 | - | 1.00 |
| Progan*** | 1=progan, 0=otherwise | binary | Farm | - | 0.10 | - | 0.30 | - | 0.00 | - | 1.00 |

*Base period 100=2002-2006
**A cash transfer to the farmer for the eligible sown area ($1,300 per rain-fed hectare up to 5 has and $963 for the remaining plots)
***A cash transfer to the farmer per head ($250-$300 per head of cattle and $93-$117 per head of pigs)
Plots=219,985-168,265. Farmers=77,758-59,443.

## Table 3.10 Multinomial Logit model 8 alternatives-2012 (unrestricted model)

| VARIABLES | beverage | cattle | cereals | fruits | other | pigs | poultry | vegetables |
|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | |
| Temperature | 3.6981*** | 0.6945*** | | -0.6485*** | 0.8785*** | 0.2738 | 2.5354*** | 0.8487*** |
| | (0.1909) | (0.0394) | | (0.0502) | (0.0601) | (0.2512) | (0.3611) | (0.2214) |
| Temperature sq. | -0.0886*** | -0.0178*** | | 0.0197*** | -0.0304*** | -0.0105** | -0.0694*** | -0.0192*** |
| | (0.0045) | (0.0010) | | (0.0012) | (0.0018) | (0.0053) | (0.0095) | (0.0063) |
| Rainfall | 0.7054*** | -0.0531* | | 0.6264*** | -1.1021*** | 0.3410 | -0.7024*** | -0.8413*** |
| | (0.0476) | (0.0309) | | (0.0430) | (0.0533) | (0.2990) | (0.2492) | (0.1541) |
| Rainfall sq. | -0.0177*** | -0.0107*** | | -0.0114*** | -0.0095*** | -0.0420*** | -0.0188** | 0.0061*** |
| | (0.0006) | (0.0004) | | (0.0008) | (0.0007) | (0.0131) | (0.0086) | (0.0014) |
| Temp.*Rainfall | 0.0091*** | 0.0211*** | | -0.0046** | 0.0615*** | 0.0170 | 0.0465*** | 0.0244*** |
| | (0.0022) | (0.0013) | | (0.0018) | (0.0027) | (0.0104) | (0.0119) | (0.0071) |
| Temperature SD | -0.1197*** | 0.0117*** | | 0.0284*** | 0.0424*** | -0.0180 | -0.0395*** | -0.0127* |
| | (0.0078) | (0.0019) | | (0.0031) | (0.0017) | (0.0158) | (0.0152) | (0.0068) |
| Rainfall seasonality | -0.0078** | -0.0132*** | | -0.0055*** | -0.0063*** | -0.0005 | -0.0159** | -0.0031 |
| | (0.0030) | (0.0010) | | (0.0020) | (0.0014) | (0.0072) | (0.0069) | (0.0031) |
| **Output prices** | | | | | | | | |
| Price beverage | -0.0044*** | -0.0078*** | | -0.0128*** | -0.0138*** | 0.0126* | -0.0006 | -0.0113*** |
| | (0.0012) | (0.0008) | | (0.0012) | (0.0009) | (0.0071) | (0.0065) | (0.0025) |
| Price cattle | 0.0026 | -0.0087*** | | -0.0180*** | 0.0253*** | -0.0076 | -0.0135 | 0.0023 |
| | (0.0043) | (0.0016) | | (0.0039) | (0.0019) | (0.0097) | (0.0083) | (0.0065) |
| Price cereals | 0.0301*** | -0.0143*** | | 0.0086*** | -0.0124*** | 0.0054 | -0.0229 | -0.0078* |
| | (0.0048) | (0.0018) | | (0.0024) | (0.0016) | (0.0084) | (0.0140) | (0.0047) |
| Price fruits | -0.0394*** | 0.0084*** | | 0.0194*** | 0.0035** | 0.0449*** | 0.0120 | 0.0093 |
| | (0.0042) | (0.0015) | | (0.0018) | (0.0017) | (0.0123) | (0.0086) | (0.0074) |
| Price other | -0.0374*** | 0.0031* | | -0.0128*** | 0.0193*** | -0.0871*** | -0.0522*** | 0.0208*** |
| | (0.0048) | (0.0017) | | (0.0029) | (0.0020) | (0.0116) | (0.0111) | (0.0058) |
| Price pigs | -0.0016 | -0.0026** | | 0.0173*** | 0.0080*** | -0.0051 | 0.0044 | -0.0060 |
| | (0.0030) | (0.0012) | | (0.0021) | (0.0015) | (0.0068) | (0.0073) | (0.0043) |
| Price poultry | 0.0078*** | 0.0047*** | | -0.0124*** | -0.0134*** | 0.0070 | 0.0098* | -0.0142*** |
| | (0.0024) | (0.0011) | | (0.0019) | (0.0014) | (0.0055) | (0.0054) | (0.0024) |
| Price vegetables | -0.0075*** | 0.0023* | | -0.0085*** | -0.0017 | -0.0038 | 0.0026 | 0.0068** |
| | (0.0026) | (0.0012) | | (0.0022) | (0.0015) | (0.0062) | (0.0056) | (0.0029) |
| **Inputs** | | | | | | | | |
| Wage rate | -0.0007 | 0.0039*** | | 0.0071*** | -0.0020*** | 0.0090*** | 0.0059*** | 0.0101*** |
| | (0.0013) | (0.0006) | | (0.0007) | (0.0007) | (0.0027) | (0.0020) | (0.0017) |
| Plot size | -0.0752*** | 0.6300*** | | 0.0487*** | -0.0069 | -0.0305 | 0.1643*** | -0.0645*** |
| | (0.0245) | (0.0113) | | (0.0171) | (0.0098) | (0.0526) | (0.0580) | (0.0247) |
| **Socio-demographic characteristics** | | | | | | | | |
| Age | 0.0146*** | 0.0124*** | | 0.0155*** | 0.0033** | 0.0018 | -0.0217*** | -0.0164*** |
| | (0.0026) | (0.0014) | | (0.0023) | (0.0017) | (0.0094) | (0.0081) | (0.0033) |
| Indigenous | -0.9534*** | -0.9506*** | | -0.8585*** | -1.4952*** | -0.3953 | -2.7135*** | -1.1277*** |
| | (0.0899) | (0.0513) | | (0.0768) | (0.0724) | (0.3443) | (1.0302) | (0.1766) |
| Schooling | 0.0138 | 0.0332*** | | 0.0491*** | 0.0321*** | 0.1567*** | 0.1452*** | -0.0116 |
| | (0.0087) | (0.0053) | | (0.0074) | (0.0047) | (0.0214) | (0.0330) | (0.0114) |
| **Access to markets** | | | | | | | | |
| Mobile | -0.1567 | -0.0274 | | 0.4550*** | 0.1182*** | 0.6128*** | 0.9256*** | 0.0881 |
| | (0.1396) | (0.0405) | | (0.0611) | (0.0398) | (0.2024) | (0.3531) | (0.0847) |
| Internet | 0.0255 | -0.4035*** | | 0.2745** | 0.0763 | 1.7746*** | 1.1179*** | 0.6325*** |
| | (0.2440) | (0.0811) | | (0.1349) | (0.1029) | (0.1790) | (0.2795) | (0.1426) |
| City | -0.0511*** | 0.0193*** | | -0.0389*** | -0.0190*** | -0.0033 | -0.0268 | 0.0204*** |
| | (0.0064) | (0.0020) | | (0.0038) | (0.0024) | (0.0162) | (0.0183) | (0.0070) |
| Road density | 2.1814*** | -0.6067*** | | -1.6999*** | -0.5731*** | 0.7520** | 1.1259*** | -0.4605* |
| | (0.1679) | (0.0803) | | (0.1376) | (0.0813) | (0.3546) | (0.3524) | (0.2783) |
| **Soils** | | | | | | | | |
| Vertisol | -0.0189*** | -0.0057*** | | -0.0057*** | -0.0037*** | -0.0149*** | -0.0069** | -0.0055*** |
| | (0.0019) | (0.0006) | | (0.0009) | (0.0005) | (0.0026) | (0.0029) | (0.0014) |
| Feozem | -0.0091*** | 0.0037*** | | 0.0062*** | -0.0008 | -0.0050* | 0.0080*** | -0.0012 |
| | (0.0018) | (0.0005) | | (0.0009) | (0.0005) | (0.0026) | (0.0026) | (0.0015) |
| Regosol | -0.0070*** | 0.0045*** | | -0.0018 | -0.0005 | -0.0125*** | -0.0132*** | 0.0079*** |
| | (0.0012) | (0.0005) | | (0.0015) | (0.0009) | (0.0032) | (0.0038) | (0.0018) |
| Cambisol | -0.0085*** | -0.0013** | | -0.0083*** | -0.0043*** | -0.0213*** | -0.0020 | 0.0010 |
| | (0.0011) | (0.0006) | | (0.0013) | (0.0008) | (0.0044) | (0.0062) | (0.0022) |
| Constant | -40.0091*** | -8.8610*** | | -0.0571 | -7.7602*** | -7.9115* | -19.1688*** | -8.8924*** |
| | (2.4237) | (0.6430) | | (1.1499) | (0.7704) | (4.4892) | (4.6236) | (1.9158) |
| Observations | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 |

Robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: cereals. SD: Standard Deviation.

## Table 3.11 Multinomial Logit model 8 alternatives-2014 (unrestricted model)

| VARIABLES | beverage | cattle | cereals | fruits | other | pigs | poultry | vegetables |
|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | |
| Temperature | 3.5001*** | 0.8627*** | | -0.7609*** | 0.5718*** | 0.9118*** | 0.7481* | 0.3252 |
| | (0.1586) | (0.0707) | | (0.0509) | (0.0803) | (0.2445) | (0.3921) | (0.2485) |
| Temperature sq. | -0.0829*** | -0.0243*** | | 0.0209*** | -0.0232*** | -0.0219*** | -0.0211** | -0.0064 |
| | (0.0038) | (0.0018) | | (0.0012) | (0.0024) | (0.0046) | (0.0102) | (0.0073) |
| Rainfall | 0.7371*** | -0.2945*** | | 0.4388*** | -1.3133*** | 0.3398 | -0.1231 | -0.5992*** |
| | (0.0594) | (0.0478) | | (0.0489) | (0.0784) | (0.3317) | (0.1692) | (0.1463) |
| Rainfall sq. | -0.0167*** | -0.0133*** | | -0.0135*** | -0.0055*** | -0.0310** | -0.0120** | 0.0065*** |
| | (0.0007) | (0.0007) | | (0.0010) | (0.0007) | (0.0139) | (0.0048) | (0.0021) |
| Temp.*Rainfall | 0.0048** | 0.0340*** | | 0.0031* | 0.0647*** | 0.0086 | 0.0235*** | 0.0136* |
| | (0.0023) | (0.0019) | | (0.0019) | (0.0036) | (0.0126) | (0.0085) | (0.0078) |
| Temperature SD | -0.1036*** | 0.0127*** | | 0.0392*** | 0.0271*** | -0.0514** | 0.0106 | -0.0397*** |
| | (0.0077) | (0.0024) | | (0.0032) | (0.0027) | (0.0201) | (0.0221) | (0.0087) |
| Rainfall seasonality | 0.0027 | -0.0023* | | -0.0156*** | 0.0011 | 0.0114** | -0.0034 | 0.0103*** |
| | (0.0030) | (0.0012) | | (0.0020) | (0.0016) | (0.0055) | (0.0081) | (0.0038) |
| **Output prices** | | | | | | | | |
| Price beverage | 0.0036** | 0.0028** | | -0.0023 | -0.0061*** | 0.0315*** | -0.0030 | 0.0042 |
| | (0.0017) | (0.0014) | | (0.0015) | (0.0017) | (0.0072) | (0.0053) | (0.0041) |
| Price cattle | 0.0001 | 0.0038** | | -0.0115*** | 0.0248*** | 0.0228*** | -0.0042 | 0.0091** |
| | (0.0034) | (0.0017) | | (0.0032) | (0.0023) | (0.0075) | (0.0084) | (0.0042) |
| Price cereals | 0.0115*** | -0.0082*** | | 0.0084*** | -0.0005 | 0.0186*** | -0.0270*** | -0.0080 |
| | (0.0037) | (0.0016) | | (0.0024) | (0.0018) | (0.0060) | (0.0094) | (0.0068) |
| Price fruits | -0.0087*** | 0.0048*** | | 0.0170*** | -0.0028 | 0.0387*** | 0.0031 | -0.0142** |
| | (0.0024) | (0.0013) | | (0.0014) | (0.0020) | (0.0073) | (0.0053) | (0.0055) |
| Price other | -0.0438*** | -0.0097*** | | -0.0010 | 0.0072*** | -0.0329*** | 0.0129 | 0.0102** |
| | (0.0039) | (0.0018) | | (0.0025) | (0.0021) | (0.0127) | (0.0080) | (0.0044) |
| Price pigs | 0.0037* | -0.0024** | | 0.0177*** | 0.0053*** | -0.0158*** | 0.0058 | -0.0056 |
| | (0.0021) | (0.0011) | | (0.0015) | (0.0011) | (0.0056) | (0.0093) | (0.0049) |
| Price poultry | -0.0006 | 0.0021 | | 0.0034** | -0.0141*** | -0.0003 | 0.0209* | -0.0061* |
| | (0.0018) | (0.0013) | | (0.0015) | (0.0011) | (0.0103) | (0.0112) | (0.0036) |
| Price vegetables | -0.0254*** | 0.0042*** | | -0.0083*** | -0.0077*** | 0.0198*** | -0.0018 | 0.0029 |
| | (0.0034) | (0.0013) | | (0.0022) | (0.0017) | (0.0037) | (0.0083) | (0.0037) |
| **Inputs** | | | | | | | | |
| Wage rate | -0.0066** | 0.0026 | | 0.0002 | 0.0026** | 0.0138** | -0.0129** | 0.0033 |
| | (0.0026) | (0.0017) | | (0.0013) | (0.0011) | (0.0057) | (0.0061) | (0.0036) |
| Plot size | -0.0744*** | 0.4802*** | | -0.0382** | -0.0188** | 0.0079 | 0.0922 | -0.0525* |
| | (0.0195) | (0.0159) | | (0.0175) | (0.0091) | (0.0486) | (0.0947) | (0.0287) |
| **Socio-demographic characteristics** | | | | | | | | |
| Age | 0.0168*** | 0.0194*** | | 0.0182*** | 0.0018 | 0.0061 | 0.0216 | -0.0135*** |
| | (0.0024) | (0.0014) | | (0.0023) | (0.0014) | (0.0058) | (0.0132) | (0.0038) |
| Indigenous | -0.5196*** | -0.4109*** | | -0.1172* | -0.1396*** | 0.0759 | -0.1402 | -0.1228 |
| | (0.0792) | (0.0572) | | (0.0599) | (0.0541) | (0.1627) | (0.3211) | (0.1297) |
| Schooling | 0.0398*** | 0.0399*** | | 0.0469*** | 0.0186*** | 0.0122 | 0.0342 | -0.0025 |
| | (0.0089) | (0.0050) | | (0.0075) | (0.0060) | (0.0230) | (0.0342) | (0.0149) |
| **Access to markets** | | | | | | | | |
| Mobile | -0.2879*** | 0.3199*** | | 0.2535*** | 0.3871*** | 0.6479*** | -0.0201 | 0.1724 |
| | (0.0979) | (0.0418) | | (0.0569) | (0.0388) | (0.1737) | (0.2879) | (0.1489) |
| Internet | 0.1004 | -0.2143** | | 0.4287*** | 0.2053** | 2.2080*** | 2.0047*** | 1.0330*** |
| | (0.2623) | (0.0951) | | (0.1164) | (0.0962) | (0.2280) | (0.4417) | (0.1442) |
| City | -0.0517*** | 0.0196*** | | -0.0554*** | -0.0062*** | -0.0173 | 0.0046 | 0.0264*** |
| | (0.0054) | (0.0024) | | (0.0040) | (0.0022) | (0.0171) | (0.0203) | (0.0097) |
| Road density | 2.3630*** | -0.7613*** | | -0.9390*** | -0.3954*** | -0.7230 | 1.0536** | -0.4358 |
| | (0.1388) | (0.1363) | | (0.1318) | (0.0937) | (0.4968) | (0.5166) | (0.3128) |
| **Soils** | | | | | | | | |
| Vertisol | -0.0150*** | -0.0032*** | | -0.0038*** | -0.0028*** | -0.0125*** | -0.0184*** | -0.0039** |
| | (0.0014) | (0.0006) | | (0.0009) | (0.0007) | (0.0021) | (0.0039) | (0.0017) |
| Feozem | -0.0095*** | 0.0045*** | | 0.0050*** | -0.0001 | -0.0046** | -0.0076* | 0.0032** |
| | (0.0016) | (0.0006) | | (0.0010) | (0.0006) | (0.0021) | (0.0044) | (0.0016) |
| Regosol | -0.0063*** | 0.0066*** | | 0.0005 | 0.0020* | -0.0104*** | -0.0054 | 0.0158*** |
| | (0.0011) | (0.0006) | | (0.0014) | (0.0011) | (0.0037) | (0.0033) | (0.0020) |
| Cambisol | -0.0013 | -0.0015** | | -0.0045*** | -0.0037*** | -0.0224*** | -0.0018 | 0.0015 |
| | (0.0010) | (0.0008) | | (0.0013) | (0.0010) | (0.0046) | (0.0081) | (0.0023) |
| Constant | -37.4120*** | -13.2594*** | | -3.5007*** | -4.0776*** | -31.3232*** | -16.1589*** | -4.1574* |
| | (2.2776) | (0.8357) | | (1.1004) | (0.8422) | (3.8244) | (5.2909) | (2.4697) |
| Observations | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 |

Robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: cereals. SD: Standard Deviation.

## Table 3.12 Multinomial Logit model 8 alternatives and subsidies (2014)

| VARIABLES | beverage | cattle | cereals | fruits | other | pigs | poultry | vegetables |
|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | |
| Temperature | 3.5455*** | 0.7721*** | | -0.7241*** | 0.4960*** | -0.1089 | 0.8317** | 0.4534* |
| | (0.1629) | (0.0681) | | (0.0504) | (0.0967) | (0.5530) | (0.4157) | (0.2489) |
| Temperature sq. | -0.0824*** | -0.0213*** | | 0.0196*** | -0.0214*** | 0.0007 | -0.0230** | -0.0107 |
| | (0.0039) | (0.0017) | | (0.0012) | (0.0030) | (0.0101) | (0.0106) | (0.0072) |
| Rainfall | 0.8167*** | -0.2572*** | | 0.4106*** | -1.4357*** | 0.0583 | -0.2165 | -0.6969*** |
| | (0.0632) | (0.0458) | | (0.0480) | (0.0798) | (0.5908) | (0.1667) | (0.1467) |
| Rainfall sq. | -0.0167*** | -0.0102*** | | -0.0144*** | -0.0044*** | -0.0241** | -0.0099** | 0.0043** |
| | (0.0007) | (0.0006) | | (0.0011) | (0.0010) | (0.0120) | (0.0044) | (0.0020) |
| Temp.*Rainfall | 0.0013 | 0.0285*** | | 0.0045** | 0.0673*** | 0.0147 | 0.0243*** | 0.0190** |
| | (0.0023) | (0.0018) | | (0.0019) | (0.0041) | (0.0206) | (0.0084) | (0.0077) |
| Temperature SD | -0.0928*** | 0.0120*** | | 0.0452*** | 0.0189*** | -0.0346 | -0.0037 | -0.0429*** |
| | (0.0055) | (0.0022) | | (0.0027) | (0.0026) | (0.0230) | (0.0237) | (0.0080) |
| Rainfall seasonality | -0.0045* | -0.0023** | | -0.0127*** | 0.0039** | 0.0052 | 0.0053 | 0.0120*** |
| | (0.0026) | (0.0010) | | (0.0018) | (0.0017) | (0.0049) | (0.0073) | (0.0033) |
| **Output prices** | | | | | | | | |
| Price beverage | 0.0038** | | | | | | | |
| | (0.0015) | | | | | | | |
| Price cattle | | -0.0047*** | | | | | | |
| | | (0.0015) | | | | | | |
| Price fruits | | | | 0.0137*** | | | | |
| | | | | (0.0013) | | | | |
| Price other | | | | | 0.0196*** | | | |
| | | | | | (0.0032) | | | |
| Price pigs | | | | | | -0.0186*** | | |
| | | | | | | (0.0069) | | |
| Price poultry | | | | | | | 0.0178 | |
| | | | | | | | (0.0121) | |
| Price vegetables | | | | | | | | 0.0008 |
| | | | | | | | | (0.0037) |
| **Inputs** | | | | | | | | |
| Wage rate | -0.0095*** | 0.0011 | | -0.0002 | 0.0019* | 0.0010 | -0.0114* | 0.0056* |
| | (0.0025) | (0.0017) | | (0.0013) | (0.0011) | (0.0075) | (0.0062) | (0.0032) |
| Plot size | -0.0646*** | 0.4428*** | | -0.0361** | -0.0058 | 0.0226 | 0.0679 | -0.0554** |
| | (0.0196) | (0.0160) | | (0.0168) | (0.0093) | (0.0459) | (0.0851) | (0.0268) |
| **Socio-demographic characteristics** | | | | | | | | |
| Age | 0.0214*** | 0.0199*** | | 0.0232*** | 0.0029** | 0.0150*** | 0.0254** | -0.0094*** |
| | (0.0024) | (0.0015) | | (0.0022) | (0.0014) | (0.0053) | (0.0126) | (0.0036) |
| Indigenous | -0.5439*** | -0.3935*** | | 0.1090* | -0.0896* | -0.0029 | -0.0735 | -0.1364 |
| | (0.0754) | (0.0576) | | (0.0568) | (0.0514) | (0.2080) | (0.3336) | (0.1228) |
| Schooling | 0.0347*** | 0.0273*** | | 0.0408*** | 0.0136** | 0.0057 | 0.0210 | -0.0054 |
| | (0.0088) | (0.0052) | | (0.0071) | (0.0069) | (0.0240) | (0.0325) | (0.0137) |
| **Access to markets** | | | | | | | | |
| Mobile | -0.2640*** | 0.2754*** | | 0.3562*** | 0.3977*** | 0.7585*** | -0.0020 | 0.2199 |
| | (0.0999) | (0.0430) | | (0.0593) | (0.0388) | (0.1879) | (0.2720) | (0.1491) |
| Internet | 0.0891 | -0.1922* | | 0.3328*** | 0.1729* | 2.0606*** | 1.9116*** | 0.9675*** |
| | (0.2489) | (0.1048) | | (0.1141) | (0.1049) | (0.3034) | (0.4257) | (0.1431) |
| City | -0.0566*** | 0.0160*** | | -0.0479*** | -0.0095*** | -0.0282* | 0.0054 | 0.0229*** |
| | (0.0051) | (0.0027) | | (0.0038) | (0.0021) | (0.0159) | (0.0182) | (0.0085) |
| Road density | 1.7509*** | -0.7262*** | | -1.4140*** | -1.3372*** | -1.4791** | 0.4319 | -0.7644*** |
| | (0.1193) | (0.1345) | | (0.1298) | (0.1134) | (0.6279) | (0.5340) | (0.2905) |
| **Soils** | | | | | | | | |
| Vertisol | -0.0177*** | -0.0039*** | | -0.0025*** | -0.0033*** | -0.0114*** | -0.0160*** | -0.0020 |
| | (0.0014) | (0.0007) | | (0.0008) | (0.0008) | (0.0021) | (0.0036) | (0.0015) |
| Feozem | -0.0126*** | 0.0029*** | | 0.0058*** | -0.0014* | -0.0053 | -0.0076* | 0.0029* |
| | (0.0016) | (0.0006) | | (0.0009) | (0.0007) | (0.0035) | (0.0041) | (0.0016) |
| Regosol | -0.0064*** | 0.0059*** | | 0.0019 | 0.0012 | -0.0106*** | -0.0052 | 0.0139*** |
| | (0.0011) | (0.0006) | | (0.0012) | (0.0012) | (0.0028) | (0.0035) | (0.0020) |
| Cambisol | -0.0019** | -0.0023*** | | -0.0029** | -0.0052*** | -0.0253*** | -0.0016 | 0.0008 |
| | (0.0009) | (0.0008) | | (0.0012) | (0.0011) | (0.0059) | (0.0083) | (0.0024) |
| **Subsidies** | | | | | | | | |
| Procampo | -1.0628*** | -0.9614*** | | -1.3716*** | -0.3810*** | -2.6072*** | -1.9681*** | -1.0401*** |
| | (0.0787) | (0.0489) | | (0.0606) | (0.0797) | (0.2488) | (0.3301) | (0.1140) |
| Progan | -0.2109 | 1.6116*** | | -0.8536*** | -0.3676*** | 0.1142 | -0.0285 | -1.3193*** |
| | (0.1752) | (0.0507) | | (0.1181) | (0.0627) | (0.3046) | (0.4536) | (0.1936) |
| Constant | -46.2435*** | -11.8502*** | | -1.8393*** | -5.4495*** | -1.4357 | -18.7662*** | -5.9295*** |
| | (1.9350) | (0.6415) | | (0.6605) | (0.4970) | (9.8406) | (5.1616) | (2.1881) |
| Observations | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 |

Robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: cereals. SD: Standard Deviation.

# Table 3.13 Multinomial Logit model 31 alternatives (1-2012)

| VARIABLES | alfalfa | apples | avocado | bananas | barley | beans | cacao | cattle | chilli | coffee |
|---|---|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | | | |
| Temperature | 5.0852*** | 2.1171** | 4.0993*** | 4.5295*** | -1.8371*** | 0.6738*** | 18.3094*** | 0.7274*** | 2.1951*** | 5.4786*** |
| | (0.2402) | (0.9647) | (0.2791) | (0.8918) | (0.1693) | (0.0654) | (4.9978) | (0.0451) | (0.2220) | (0.2732) |
| Temperature sq. | -0.1256*** | -0.0918*** | -0.1194*** | -0.0672*** | 0.0464*** | -0.0329*** | -0.3524*** | -0.0170*** | -0.0739*** | -0.1306*** |
| | (0.0055) | (0.0308) | (0.0089) | (0.0170) | (0.0032) | (0.0020) | (0.0989) | (0.0012) | (0.0068) | (0.0064) |
| Rainfall | 1.2842*** | -0.4379 | 3.5350*** | 1.7239*** | 2.8141*** | -2.3023*** | 0.5435 | 0.0717** | -4.0295*** | 0.7579*** |
| | (0.3153) | (0.3098) | (0.4195) | (0.1870) | (0.8122) | (0.0689) | (0.4375) | (0.0340) | (0.2833) | (0.0536) |
| Rainfall sq. | -0.0497*** | -0.0072 | -0.1346*** | -0.0059*** | -0.2361*** | -0.0028** | -0.0212*** | -0.0108*** | -0.0383** | -0.0157*** |
| | (0.0121) | (0.0086) | (0.0235) | (0.0012) | (0.0595) | (0.0011) | (0.0020) | (0.0005) | (0.0156) | (0.0007) |
| Temp.*Rainfall | -0.0740*** | 0.0418** | -0.0119 | -0.0563*** | -0.0508*** | 0.0954*** | 0.0184 | 0.0150*** | 0.1856*** | 0.0033 |
| | (0.0125) | (0.0209) | (0.0237) | (0.0069) | (0.0184) | (0.0035) | (0.0171) | (0.0016) | (0.0186) | (0.0025) |
| Temperature SD | 0.0466*** | 0.0788*** | -0.1182*** | -0.0679*** | -0.0479*** | -0.0265*** | -0.0395* | 0.0208*** | 0.0086 | -0.0776*** |
| | (0.0039) | (0.0097) | (0.0211) | (0.0105) | (0.0141) | (0.0029) | (0.0221) | (0.0019) | (0.0079) | (0.0067) |
| Rainfall seasonality | -0.0132*** | -0.0119 | 0.0939*** | -0.0333*** | -0.0625*** | 0.0453*** | -0.0252*** | -0.0185*** | -0.0026 | 0.0015 |
| | (0.0039) | (0.0089) | (0.0075) | (0.0061) | (0.0109) | (0.0020) | (0.0054) | (0.0011) | (0.0028) | (0.0030) |
| **Output prices** | | | | | | | | | | |
| Price alfalfa | 0.0081*** | | | | | | | | | |
| | (0.0011) | | | | | | | | | |
| Price apples | | 0.0150*** | | | | | | | | |
| | | (0.0018) | | | | | | | | |
| Price avocado | | | 0.0005 | | | | | | | |
| | | | (0.0008) | | | | | | | |
| Price bananas | | | | 0.0053*** | | | | | | |
| | | | | (0.0019) | | | | | | |
| Price barley | | | | | 0.0059* | | | | | |
| | | | | | (0.0033) | | | | | |
| Price beans | | | | | | 0.0048*** | | | | |
| | | | | | | (0.0005) | | | | |
| Price cacao | | | | | | | 0.0133*** | | | |
| | | | | | | | (0.0021) | | | |
| Price cattle | | | | | | | | -0.0179*** | | |
| | | | | | | | | (0.0013) | | |
| Price chilli | | | | | | | | | -0.0092*** | |
| | | | | | | | | | (0.0016) | |
| Price coffee | | | | | | | | | | -0.0000 |
| | | | | | | | | | | (0.0007) |
| **Inputs** | | | | | | | | | | |
| Wage rate | -0.0009 | -0.0047 | 0.0080*** | 0.0141*** | 0.0019* | -0.0077*** | -0.0074*** | 0.0029*** | -0.0065*** | 0.0015 |
| | (0.0010) | (0.0048) | (0.0016) | (0.0016) | (0.0011) | (0.0011) | (0.0024) | (0.0006) | (0.0022) | (0.0016) |
| Plot size | -0.0216 | -0.1061*** | 0.0457 | 0.0172 | 0.2023*** | -0.0451*** | -0.2710*** | 0.6483*** | 0.1230*** | -0.0348 |
| | (0.0213) | (0.0370) | (0.0357) | (0.0359) | (0.0229) | (0.0116) | (0.0406) | (0.0122) | (0.0278) | (0.0283) |
| **Socio-demographic characteristics** | | | | | | | | | | |
| Age | 0.0108*** | 0.0435*** | 0.0141*** | 0.0096* | 0.0117*** | 0.0025 | 0.0162*** | 0.0139*** | -0.0196*** | 0.0153*** |
| | (0.0032) | (0.0062) | (0.0039) | (0.0051) | (0.0030) | (0.0016) | (0.0055) | (0.0016) | (0.0033) | (0.0030) |
| Indigenous | 0.4927*** | -1.3186** | -1.7970*** | -1.7038*** | -2.0915*** | -0.4490*** | -2.6563*** | -1.3543*** | -0.9912*** | -0.8810*** |
| | (0.1103) | (0.5824) | (0.2324) | (0.2250) | (0.3403) | (0.0932) | (0.3679) | (0.0524) | (0.2359) | (0.0949) |
| Schooling | 0.0402*** | 0.1342*** | 0.0459*** | 0.0475*** | 0.0427*** | 0.0139** | -0.0162 | 0.0406*** | -0.0129 | 0.0428*** |
| | (0.0100) | (0.0165) | (0.0138) | (0.0142) | (0.0104) | (0.0055) | (0.0163) | (0.0058) | (0.0105) | (0.0098) |
| **Access to markets** | | | | | | | | | | |
| Mobile | 0.4343*** | -0.0952 | 0.7781*** | 1.2565*** | 0.5782*** | 0.1285*** | -0.3342* | 0.0417 | 0.6233*** | 0.1638 |
| | (0.0663) | (0.1408) | (0.1189) | (0.1485) | (0.0984) | (0.0471) | (0.1949) | (0.0440) | (0.0904) | (0.1728) |
| Internet | -0.2653* | 0.5657** | 0.7152*** | 0.7551*** | 0.2647 | -0.4389*** | -0.4306 | -0.4073*** | -0.0271 | 0.2822 |
| | (0.1501) | (0.2424) | (0.2149) | (0.2708) | (0.2065) | (0.1290) | (0.6995) | (0.1088) | (0.1702) | (0.2465) |
| City | -0.0230*** | -0.0287*** | -0.0632*** | -0.0730*** | -0.0260** | -0.0228*** | -0.1329*** | 0.0125*** | -0.0309*** | -0.0335*** |
| | (0.0077) | (0.0066) | (0.0126) | (0.0111) | (0.0108) | (0.0026) | (0.0169) | (0.0021) | (0.0084) | (0.0064) |
| Road density | 0.7815*** | -4.1531*** | -3.5183*** | 2.0493*** | -0.8785*** | -4.4594*** | 3.6717*** | -0.4495*** | -1.8275*** | 1.6863*** |
| | (0.1391) | (0.4101) | (0.4043) | (0.2073) | (0.1678) | (0.1548) | (0.3285) | (0.0849) | (0.3129) | (0.1778) |
| **Soils** | | | | | | | | | | |
| Vertisol | 0.0080*** | 0.0168*** | -0.0119** | 0.0033 | 0.0079*** | -0.0033*** | -0.0033 | -0.0029*** | -0.0049*** | -0.0227*** |
| | (0.0009) | (0.0023) | (0.0060) | (0.0026) | (0.0023) | (0.0008) | (0.0027) | (0.0007) | (0.0018) | (0.0025) |
| Feozem | 0.0093*** | 0.0068*** | -0.0130*** | 0.0243*** | 0.0207*** | -0.0012* | -11.5124*** | 0.0062*** | 0.0031** | -0.0049*** |
| | (0.0009) | (0.0019) | (0.0021) | (0.0025) | (0.0015) | (0.0006) | (1.8038) | (0.0005) | (0.0014) | (0.0017) |
| Regosol | 0.0136*** | -0.0060* | -0.0191*** | 0.0051 | 0.0066*** | -0.0128*** | -0.0447*** | 0.0054*** | 0.0043*** | -0.0074*** |
| | (0.0015) | (0.0034) | (0.0025) | (0.0032) | (0.0017) | (0.0009) | (0.0133) | (0.0005) | (0.0017) | (0.0012) |
| Cambisol | 0.0197*** | -0.0130** | -0.0102*** | 0.0098*** | 0.0082*** | 0.0038*** | -0.0117*** | 0.0009 | -0.0025 | -0.0059*** |
| | (0.0015) | (0.0055) | (0.0022) | (0.0024) | (0.0017) | (0.0008) | (0.0019) | (0.0007) | (0.0029) | (0.0013) |
| | - | - | - | - | | | - | | - | - |
| Constant | 54.0524*** | 21.2258*** | 62.2618*** | 76.3736*** | 14.1271*** | -2.5136*** | 249.8874*** | -9.9223*** | 12.1430*** | 66.0942*** |
| | (2.8948) | (7.7489) | (3.6192) | (11.8477) | (3.0196) | (0.5793) | (63.0088) | (0.4543) | (1.8877) | (2.9755) |
| Observations | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 |

Robust standard errors in parentheses (clusters at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: maize. SD: Standard Deviation.

# Table 3.14 Multinomial Logit model 31 alternatives (2-2012)

| VARIABLES | cotton | grape | gretom | lemon | mango | melon | oat | onion | oranges | pigs |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Climate | | | | | |
| Temperature | 1.6451* | 5.7000*** | 1.0535*** | 3.6633*** | 3.5286*** | -0.4552 | 1.7903*** | 3.3870*** | 6.0459*** | -0.6633 |
| | (0.8673) | (1.6030) | (0.2417) | (0.6479) | (0.5641) | (0.9611) | (0.1868) | (0.4164) | (1.0499) | (0.5093) |
| Temperature sq. | -0.0504*** | -0.1193*** | -0.0368*** | -0.0502*** | -0.0586*** | 0.0046 | -0.0482*** | -0.0835*** | -0.1319*** | 0.0158 |
| | (0.0170) | (0.0349) | (0.0062) | (0.0118) | (0.0112) | (0.0253) | (0.0044) | (0.0102) | (0.0245) | (0.0105) |
| Rainfall | -3.4328 | 12.4003*** | -0.8204*** | 1.8106*** | 0.9682** | -7.3378*** | 1.9657*** | -1.4900*** | -0.0061 | 0.0117 |
| | (4.5984) | (3.7514) | (0.1993) | (0.1713) | (0.4237) | (0.9309) | (0.2462) | (0.4539) | (0.2564) | (0.4272) |
| Rainfall sq. | -0.5185 | -0.7661*** | -0.0164*** | 0.0022* | -0.0209*** | -0.1331*** | 0.0041 | 0.0017 | -0.0199*** | -0.0058 |
| | (0.3336) | (0.2239) | (0.0039) | (0.0012) | (0.0037) | (0.0480) | (0.0083) | (0.0040) | (0.0022) | (0.0065) |
| Temp.*Rainfall | 0.1788 | -0.4929*** | 0.0555*** | -0.0806*** | -0.0084 | 0.2947*** | -0.1482*** | 0.0532** | 0.0262** | 0.0053 |
| | (0.1561) | (0.1396) | (0.0103) | (0.0070) | (0.0141) | (0.0520) | (0.0106) | (0.0211) | (0.0112) | (0.0164) |
| Temperature SD | 0.1683*** | -0.0020 | -0.0248** | -0.0941*** | -0.0113 | -0.0120 | 0.0084* | -0.0253* | 0.0725*** | -0.0134 |
| | (0.0134) | (0.0089) | (0.0115) | (0.0104) | (0.0077) | (0.0138) | (0.0047) | (0.0134) | (0.0095) | (0.0197) |
| Rainfall seasonality | -0.0400*** | 0.0143 | 0.0149* | -0.0504*** | 0.0854*** | -0.0764*** | 0.0111*** | -0.0477*** | -0.0776*** | -0.0082 |
| | (0.0088) | (0.0108) | (0.0080) | (0.0056) | (0.0044) | (0.0109) | (0.0040) | (0.0049) | (0.0036) | (0.0062) |
| | | | | | Output prices | | | | | |
| Price cotton | 0.0071 | | | | | | | | | |
| | (0.0076) | | | | | | | | | |
| Price grape | | -0.0113*** | | | | | | | | |
| | | (0.0025) | | | | | | | | |
| Price gretom | | | -0.0042 | | | | | | | |
| | | | (0.0033) | | | | | | | |
| Price lemon | | | | 0.0048*** | | | | | | |
| | | | | (0.0006) | | | | | | |
| Price mango | | | | | -0.0172*** | | | | | |
| | | | | | (0.0024) | | | | | |
| Price melon | | | | | | 0.0172*** | | | | |
| | | | | | | (0.0039) | | | | |
| Price oat | | | | | | | -0.0035*** | | | |
| | | | | | | | (0.0009) | | | |
| Price onion | | | | | | | | 0.0024** | | |
| | | | | | | | | (0.0012) | | |
| Price oranges | | | | | | | | | -0.0039*** | |
| | | | | | | | | | (0.0014) | |
| Price pigs | | | | | | | | | | -0.0315*** |
| | | | | | | | | | | (0.0082) |
| | | | | | Inputs | | | | | |
| Wage rate | -0.0605*** | 0.0276*** | -0.0148** | -0.0059*** | 0.0034** | 0.0110 | 0.0023** | 0.0114*** | 0.0037** | 0.0111*** |
| | (0.0085) | (0.0034) | (0.0058) | (0.0021) | (0.0017) | (0.0068) | (0.0010) | (0.0015) | (0.0018) | (0.0033) |
| Plot size | 0.1091*** | 0.0935 | -0.0113 | 0.0844*** | 0.0881*** | -0.2374*** | 0.0167 | 0.0463 | 0.0656** | 0.0923 |
| | (0.0368) | (0.1326) | (0.0526) | (0.0315) | (0.0307) | (0.0632) | (0.0158) | (0.0450) | (0.0272) | (0.0631) |
| | | | | | Socio-demographic characteristics | | | | | |
| Age | -0.0115 | 0.0083 | -0.0181*** | 0.0050 | 0.0287*** | -0.0290*** | 0.0045* | -0.0116 | 0.0180*** | 0.0057 |
| | (0.0072) | (0.0104) | (0.0068) | (0.0055) | (0.0067) | (0.0065) | (0.0024) | (0.0076) | (0.0039) | (0.0099) |
| Indigenous | -24.2405*** | -26.0578*** | -0.2573 | -1.9827*** | -2.0424*** | -28.7137*** | -0.6413*** | -2.6149*** | -0.8259*** | -0.6606* |
| | (0.5643) | (0.3833) | (0.4366) | (0.2403) | (0.2769) | (0.2681) | (0.1176) | (0.7426) | (0.1584) | (0.3439) |
| Schooling | -0.0238 | 0.0413 | -0.0267 | 0.0275 | 0.0923*** | -0.1223*** | 0.0519*** | -0.0189 | 0.0678*** | 0.1896*** |
| | (0.0310) | (0.0374) | (0.0226) | (0.0168) | (0.0192) | (0.0396) | (0.0071) | (0.0194) | (0.0119) | (0.0436) |
| | | | | | Access to markets | | | | | |
| Mobile | 0.2160 | -0.9253*** | 0.7855*** | 0.8091*** | 0.3790*** | -0.8095*** | 0.2984*** | 0.6996*** | -0.0380 | 0.6494*** |
| | (0.2069) | (0.2569) | (0.1951) | (0.1428) | (0.1332) | (0.1801) | (0.0649) | (0.2061) | (0.1335) | (0.1952) |
| Internet | -0.5925** | 1.0758*** | 1.0923*** | 0.1343 | -0.2746 | -0.8982 | -0.5148*** | 0.9783*** | 0.2512 | 1.7398*** |
| | (0.2717) | (0.3671) | (0.3110) | (0.2606) | (0.4027) | (0.6236) | (0.1454) | (0.2186) | (0.2216) | (0.1800) |
| City | -0.0206*** | -0.0451*** | -0.1020*** | -0.0648*** | -0.0123 | 0.0053 | -0.0012 | -0.0502*** | -0.0689*** | -0.0090 |
| | (0.0054) | (0.0146) | (0.0187) | (0.0070) | (0.0083) | (0.0074) | (0.0027) | (0.0137) | (0.0082) | (0.0126) |
| Road density | -2.5372*** | -2.9642*** | -0.3531 | 0.0233 | -1.8920*** | 2.6007*** | -1.6683*** | -0.2049 | 1.4116*** | -0.2929 |
| | (0.7518) | (0.7402) | (0.2894) | (0.2617) | (0.4319) | (0.8681) | (0.1221) | (0.4090) | (0.2619) | (0.4853) |
| | | | | | Soils | | | | | |
| Vertisol | -0.0209*** | -0.0090 | -0.0041 | 0.0100*** | -0.0094*** | -0.0610*** | 0.0095*** | 0.0203*** | 0.0150*** | -0.0130*** |
| | (0.0053) | (0.0070) | (0.0033) | (0.0021) | (0.0026) | (0.0165) | (0.0009) | (0.0025) | (0.0014) | (0.0027) |
| Feozem | -0.0065 | -0.0081 | 0.0093*** | 0.0255*** | -0.0021 | -0.0012 | 0.0043*** | 0.0160*** | 0.0319*** | -0.0043 |
| | (0.0060) | (0.0082) | (0.0031) | (0.0020) | (0.0023) | (0.0062) | (0.0007) | (0.0033) | (0.0018) | (0.0029) |
| Regosol | 0.0061*** | 0.0150*** | 0.0071** | 0.0094*** | -0.0254*** | 0.0026 | -0.0036** | 0.0297*** | 0.0069*** | -0.0120*** |
| | (0.0023) | (0.0056) | (0.0030) | (0.0021) | (0.0021) | (0.0039) | (0.0014) | (0.0031) | (0.0019) | (0.0033) |
| Cambisol | 0.0419*** | -63.3617*** | 0.0045 | 0.0048* | -0.0284*** | -0.0123 | -0.0025 | 0.0003 | 0.0031 | -0.0243*** |
| | (0.0071) | (5.0110) | (0.0038) | (0.0028) | (0.0025) | (0.0102) | (0.0017) | (0.0075) | (0.0033) | (0.0058) |
| Constant | -14.1815 | -71.5754*** | -11.4375*** | -56.4300*** | -66.5880*** | 15.7038 | -17.6767*** | -32.4719*** | -73.5980*** | 2.4164 |
| | (13.9127) | (19.7020) | (1.8760) | (8.8435) | (7.4666) | (9.6733) | (2.1074) | (4.5603) | (10.9736) | (7.4115) |
| Observations | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 |

Robust standard errors in parentheses (clusters at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: maize. SD: Standard Deviation.

# Table 3.15 Multinomial Logit model 31 alternatives (3-2012)

| VARIABLES | potato | poultry | redtom | rice | sorghum | soy | squash | sugarc | waterm | wheat |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Climate** | | | | | |
| Temperature | -1.1215* | 2.4906*** | 1.5700*** | 2.7759*** | 4.9280*** | 29.0960*** | 0.2982* | 6.3458*** | 6.5057*** | 3.1914*** |
| | (0.5841) | (0.4149) | (0.2285) | (0.5220) | (0.2423) | (5.3194) | (0.1744) | (0.2399) | (1.4276) | (0.4219) |
| Temperature sq. | 0.0460*** | -0.0634*** | -0.0383*** | -0.0322*** | -0.1303*** | -0.6842*** | -0.0034 | -0.1406*** | -0.1613*** | -0.0342*** |
| | (0.0100) | (0.0105) | (0.0064) | (0.0094) | (0.0062) | (0.1244) | (0.0051) | (0.0063) | (0.0366) | (0.0080) |
| Rainfall | 3.9766*** | -0.5117** | -0.8381*** | 3.8922*** | -2.3928*** | -15.6709*** | -0.0274 | 0.2864** | -4.9244*** | 9.5609*** |
| | (1.3293) | (0.2338) | (0.2530) | (0.5294) | (0.1698) | (2.5282) | (0.2215) | (0.1174) | (0.8555) | (0.8573) |
| Rainfall sq. | -0.1102** | -0.0100** | 0.0020 | -0.0639*** | -0.0769*** | -0.1741*** | 0.0038 | -0.0249*** | -0.0208** | -0.2699*** |
| | (0.0503) | (0.0048) | (0.0019) | (0.0119) | (0.0050) | (0.0275) | (0.0057) | (0.0041) | (0.0088) | (0.0321) |
| Temp.*Rainfall | -0.1620*** | 0.0314*** | 0.0300*** | -0.0886*** | 0.1503*** | 0.7504*** | -0.0091 | 0.0236*** | 0.2143*** | -0.4104*** |
| | (0.0436) | (0.0116) | (0.0101) | (0.0138) | (0.0078) | (0.1191) | (0.0127) | (0.0087) | (0.0414) | (0.0324) |
| Temperature SD | 0.0139 | -0.0260* | -0.0221* | -0.0693*** | 0.0436*** | 0.0751*** | -0.0059 | 0.0281*** | 0.0713*** | 0.0843*** |
| | (0.0153) | (0.0156) | (0.0119) | (0.0129) | (0.0032) | (0.0095) | (0.0128) | (0.0063) | (0.0076) | (0.0064) |
| Rainfall seasonality | -0.0442*** | -0.0285*** | 0.0064 | 0.0526*** | -0.0144*** | -0.0107** | -0.0067 | 0.0054 | 0.0152*** | -0.0265*** |
| | (0.0096) | (0.0067) | (0.0046) | (0.0055) | (0.0018) | (0.0052) | (0.0066) | (0.0034) | (0.0058) | (0.0036) |
| | | | | | **Output prices** | | | | | |
| Price potato | -0.0024 | | | | | | | | | |
| | (0.0039) | | | | | | | | | |
| Price poultry | | 0.0219*** | | | | | | | | |
| | | (0.0072) | | | | | | | | |
| Price redtom | | | -0.0015 | | | | | | | |
| | | | (0.0015) | | | | | | | |
| Price rice | | | | 0.0460*** | | | | | | |
| | | | | (0.0032) | | | | | | |
| Price sorghum | | | | | 0.0112*** | | | | | |
| | | | | | (0.0007) | | | | | |
| Price soy | | | | | | -0.0138*** | | | | |
| | | | | | | (0.0026) | | | | |
| Price squash | | | | | | | 0.0004 | | | |
| | | | | | | | (0.0025) | | | |
| Price sugarc | | | | | | | | 0.0081*** | | |
| | | | | | | | | (0.0012) | | |
| Price waterm | | | | | | | | | -0.0009 | |
| | | | | | | | | | (0.0024) | |
| Price wheat | | | | | | | | | | -0.0312*** |
| | | | | | | | | | | (0.0024) |
| | | | | | **Inputs** | | | | | |
| Wage rate | 0.0116*** | 0.0065*** | 0.0021 | 0.0012 | -0.0044*** | -0.0200*** | 0.0038* | 0.0007 | 0.0064 | -0.0085*** |
| | (0.0022) | (0.0021) | (0.0025) | (0.0031) | (0.0013) | (0.0032) | (0.0023) | (0.0013) | (0.0052) | (0.0030) |
| Plot size | 0.1634*** | 0.2383*** | 0.0556* | 0.2922*** | 0.0543*** | 0.2938*** | -0.0810 | 0.0646*** | -0.1000** | 0.1473*** |
| | (0.0491) | (0.0537) | (0.0335) | (0.0470) | (0.0163) | (0.0496) | (0.0546) | (0.0188) | (0.0455) | (0.0257) |
| | | | | | **Socio-demographic characteristics** | | | | | |
| Age | 0.0050 | -0.0204*** | -0.0109** | 0.0014 | 0.0018 | 0.0008 | -0.0202*** | 0.0118* | -0.0126 | 0.0079** |
| | (0.0113) | (0.0079) | (0.0055) | (0.0065) | (0.0024) | (0.0065) | (0.0068) | (0.0062) | (0.0155) | (0.0039) |
| Indigenous | -2.1912*** | -3.2391*** | -1.9391*** | -1.3869*** | -3.1761*** | -1.3773*** | -0.3165 | -2.1231*** | -2.0952*** | -0.5222* |
| | (0.4946) | (1.0231) | (0.3071) | (0.4769) | (0.2306) | (0.2365) | (0.3241) | (0.0966) | (0.4673) | (0.2756) |
| Schooling | 0.0753*** | 0.1517*** | 0.0433*** | 0.0238 | 0.0034 | 0.0036 | 0.0212 | 0.0762*** | -0.0540** | -0.0068 |
| | (0.0253) | (0.0333) | (0.0127) | (0.0187) | (0.0072) | (0.0214) | (0.0230) | (0.0086) | (0.0255) | (0.0130) |
| | | | | | **Access to markets** | | | | | |
| Mobile | 0.3432 | 0.9645*** | 0.4362*** | 0.5745*** | 0.3456*** | 1.3435*** | -0.1935 | 0.0210 | 0.2354 | 0.5057*** |
| | (0.2662) | (0.3302) | (0.1085) | (0.1832) | (0.0564) | (0.2040) | (0.2010) | (0.1223) | (0.2469) | (0.1114) |
| Internet | 1.1023*** | 1.1398*** | 0.9373*** | -0.7237 | -0.1849 | 0.2818 | 0.7433** | 0.2084 | -0.6564 | -0.5985*** |
| | (0.2908) | (0.2939) | (0.1798) | (0.5944) | (0.1311) | (0.3102) | (0.3066) | (0.4042) | (0.5616) | (0.1534) |
| City | -0.0097 | -0.0343* | 0.0211*** | -0.0444*** | -0.0073** | 0.0269*** | 0.0215** | -0.0501*** | 0.0015 | -0.0338*** |
| | (0.0177) | (0.0180) | (0.0073) | (0.0152) | (0.0032) | (0.0077) | (0.0086) | (0.0063) | (0.0105) | (0.0066) |
| Road density | -1.3366*** | 0.8948** | -1.4754*** | 2.4538*** | 0.8171*** | 3.0381*** | -0.7549 | 0.4213*** | -2.2017** | 0.5169*** |
| | (0.3735) | (0.3660) | (0.4246) | (0.3839) | (0.1574) | (0.4008) | (0.6510) | (0.1350) | (1.0600) | (0.1823) |
| | | | | | **Soils** | | | | | |
| Vertisol | 0.0148*** | -0.0054* | 0.0015 | 0.0059*** | 0.0096*** | 0.0153*** | -0.0009 | 0.0005 | -0.0390*** | 0.0172*** |
| | (0.0026) | (0.0030) | (0.0020) | (0.0019) | (0.0008) | (0.0017) | (0.0033) | (0.0021) | (0.0078) | (0.0015) |
| Feozem | -0.0043 | 0.0094*** | 0.0058*** | -0.0025 | 0.0059*** | 0.0136*** | -0.0018 | 0.0060*** | -0.0021 | 0.0217*** |
| | (0.0028) | (0.0027) | (0.0016) | (0.0038) | (0.0008) | (0.0038) | (0.0021) | (0.0017) | (0.0034) | (0.0014) |
| Regosol | -0.0024 | -0.0090** | 0.0117*** | -0.0219*** | -0.0040*** | -0.0078* | 0.0044* | -0.0136*** | -0.0075** | 0.0096*** |
| | (0.0053) | (0.0037) | (0.0016) | (0.0027) | (0.0012) | (0.0044) | (0.0023) | (0.0013) | (0.0035) | (0.0018) |
| Cambisol | -0.0094* | 0.0014 | 0.0060* | -0.0132*** | 0.0149*** | -0.0942*** | -0.0072 | -0.0165*** | -0.0005 | 0.0282*** |
| | (0.0054) | (0.0077) | (0.0031) | (0.0034) | (0.0010) | (0.0253) | (0.0050) | (0.0023) | (0.0032) | (0.0015) |
| Constant | -1.0356 | -30.8938*** | -18.555*** | -75.1618*** | -50.8388*** | -316.439*** | -6.5322*** | -80.2597*** | -69.8867*** | -50.708*** |
| | (8.4091) | (4.4320) | (1.7099) | (7.5379) | (2.2689) | (57.3619) | (2.0511) | (2.4243) | (13.5727) | (5.5319) |
| Observations | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 | 219,985 |

Robust standard errors in parentheses (clusters at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: maize. SD: Standard Deviation.

## Table 3.16 Multinomial Logit model 31 alternatives (1-2014)

| VARIABLES | alfalfa | apples | avocado | bananas | barley | beans | cacao | cattle | chilli | coffee |
|---|---|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | | | |
| Temperature | 5.1907*** | 0.8744* | 3.1476*** | 1.8516*** | -1.4325*** | 0.1550** | 50.5711*** | 0.7284*** | 1.0432*** | 5.2575*** |
| | (0.2548) | (0.4568) | (0.2546) | (0.3549) | (0.2173) | (0.0628) | (11.8883) | (0.0729) | (0.1896) | (0.2360) |
| Temperature sq. | -0.1277*** | -0.0494*** | -0.0918*** | -0.0151** | 0.0331*** | -0.0157*** | -0.9674*** | -0.0175*** | -0.0351*** | -0.1214*** |
| | (0.0061) | (0.0136) | (0.0085) | (0.0070) | (0.0033) | (0.0019) | (0.2285) | (0.0019) | (0.0056) | (0.0055) |
| Rainfall | 0.9761*** | -0.4393 | 4.0983*** | 1.7380*** | 1.3756*** | -1.7929*** | 0.8362 | -0.0396 | -2.0035*** | 0.9900*** |
| | (0.3373) | (0.4396) | (0.4830) | (0.1142) | (0.3286) | (0.0763) | (1.1168) | (0.0492) | (0.3654) | (0.0758) |
| Rainfall sq. | -0.0354*** | -0.0307 | -0.1789*** | -0.0102*** | -0.1258*** | 0.0051*** | -0.0224*** | -0.0110*** | -0.0009 | -0.0158*** |
| | (0.0128) | (0.0389) | (0.0285) | (0.0014) | (0.0376) | (0.0009) | (0.0033) | (0.0007) | (0.0026) | (0.0008) |
| Temp.*Rainfall | -0.0727*** | 0.0475** | -0.0042 | -0.0534*** | -0.0218 | 0.0652*** | 0.0081 | 0.0196*** | 0.0819*** | -0.0080*** |
| | (0.0133) | (0.0192) | (0.0187) | (0.0041) | (0.0255) | (0.0038) | (0.0444) | (0.0021) | (0.0163) | (0.0029) |
| Temperature SD | 0.0485*** | 0.0571*** | -0.0527*** | -0.0531*** | -0.0533*** | -0.0386*** | -0.0405 | 0.0373*** | 0.0341*** | -0.0710*** |
| | (0.0050) | (0.0099) | (0.0150) | (0.0089) | (0.0087) | (0.0031) | (0.0330) | (0.0022) | (0.0075) | (0.0060) |
| Rainfall seasonality | 0.0028 | -0.0089 | 0.0629*** | -0.0560*** | -0.0555*** | 0.0461*** | -0.0414*** | -0.0097*** | 0.0101** | -0.0061** |
| | (0.0040) | (0.0064) | (0.0089) | (0.0056) | (0.0051) | (0.0019) | (0.0091) | (0.0011) | (0.0041) | (0.0031) |
| **Output prices** | | | | | | | | | | |
| Price alfalfa | 0.0054*** | | | | | | | | | |
| | (0.0013) | | | | | | | | | |
| Price apples | | 0.0217*** | | | | | | | | |
| | | (0.0015) | | | | | | | | |
| Price avocado | | | 0.0005 | | | | | | | |
| | | | (0.0005) | | | | | | | |
| Price bananas | | | | 0.0011 | | | | | | |
| | | | | (0.0012) | | | | | | |
| Price barley | | | | | 0.0166*** | | | | | |
| | | | | | (0.0033) | | | | | |
| Price beans | | | | | | 0.0042*** | | | | |
| | | | | | | (0.0004) | | | | |
| Price cacao | | | | | | | -0.0008 | | | |
| | | | | | | | (0.0056) | | | |
| Price cattle | | | | | | | | -0.0050*** | | |
| | | | | | | | | (0.0015) | | |
| Price chilli | | | | | | | | | -0.0049*** | |
| | | | | | | | | | (0.0017) | |
| Price coffee | | | | | | | | | | -0.0017*** |
| | | | | | | | | | | (0.0006) |
| **Inputs** | | | | | | | | | | |
| Wage rate | -0.0182*** | 0.0054 | 0.0182*** | 0.0088*** | -0.0044 | 0.0016 | -0.0672** | -0.0018 | -0.0243*** | -0.0081*** |
| | (0.0035) | (0.0045) | (0.0026) | (0.0025) | (0.0053) | (0.0015) | (0.0269) | (0.0016) | (0.0048) | (0.0026) |
| Plot size | -0.0207 | -0.1007*** | -0.0703** | -0.0771*** | 0.1179*** | -0.0409*** | -0.2292*** | 0.5176*** | 0.1502*** | -0.0361* |
| | (0.0201) | (0.0332) | (0.0350) | (0.0284) | (0.0334) | (0.0107) | (0.0483) | (0.0156) | (0.0374) | (0.0211) |
| **Socio-demographic characteristics** | | | | | | | | | | |
| Age | 0.0048* | 0.0357*** | 0.0218*** | 0.0203*** | 0.0176*** | 0.0047*** | 0.0389*** | 0.0226*** | -0.0145*** | 0.0179*** |
| | (0.0027) | (0.0051) | (0.0045) | (0.0040) | (0.0039) | (0.0018) | (0.0065) | (0.0015) | (0.0041) | (0.0026) |
| Indigenous | 0.6522*** | -0.5744 | -0.5674*** | -1.3517*** | -1.1548*** | -0.0642 | -1.6988*** | -0.6118*** | 0.5058*** | -0.6596*** |
| | (0.0897) | (0.3503) | (0.1615) | (0.1372) | (0.1976) | (0.0716) | (0.2027) | (0.0561) | (0.1586) | (0.0840) |
| Schooling | 0.0568*** | 0.1605*** | 0.0402*** | 0.0485*** | 0.0641*** | 0.0172*** | 0.0423** | 0.0590*** | 0.0064 | 0.0557*** |
| | (0.0118) | (0.0156) | (0.0134) | (0.0128) | (0.0124) | (0.0067) | (0.0205) | (0.0057) | (0.0177) | (0.0104) |
| **Access to markets** | | | | | | | | | | |
| Mobile | 0.5141*** | 0.1921 | 0.8954*** | 0.5954*** | 0.4877*** | 0.1113** | -1.0767*** | 0.4105*** | 0.5944*** | -0.0044 |
| | (0.1050) | (0.1534) | (0.1430) | (0.1269) | (0.1204) | (0.0505) | (0.2481) | (0.0440) | (0.1458) | (0.1065) |
| Internet | -0.0391 | 0.9085*** | 0.8537*** | 1.0276*** | 0.3113 | -0.3887*** | -0.6519 | -0.4246*** | 0.5550*** | 0.1717 |
| | (0.1507) | (0.2009) | (0.2456) | (0.2333) | (0.2458) | (0.1170) | (0.7564) | (0.1037) | (0.1491) | (0.2662) |
| City | -0.0209** | -0.0351*** | -0.0378*** | -0.1175*** | -0.0171* | -0.0079*** | -0.1448*** | 0.0145*** | -0.0195*** | -0.0521*** |
| | (0.0088) | (0.0065) | (0.0113) | (0.0113) | (0.0095) | (0.0023) | (0.0236) | (0.0024) | (0.0066) | (0.0054) |
| Road density | 0.9681*** | -6.5739*** | -2.0722*** | 1.7213*** | -1.1141*** | -4.7572*** | 3.7556*** | -0.6252*** | -1.7364*** | 2.0924*** |
| | (0.2028) | (0.6082) | (0.3778) | (0.2067) | (0.2945) | (0.1867) | (0.3751) | (0.1319) | (0.3730) | (0.1426) |
| **Soils** | | | | | | | | | | |
| Vertisol | 0.0066*** | 0.0219*** | -0.0287*** | 0.0046** | 0.0160*** | -0.0004 | -0.0088*** | 0.0003 | 0.0015 | -0.0165*** |
| | (0.0011) | (0.0018) | (0.0042) | (0.0021) | (0.0021) | (0.0009) | (0.0033) | (0.0007) | (0.0026) | (0.0015) |
| Feozem | 0.0082*** | 0.0027 | -0.0158*** | 0.0227*** | 0.0131*** | 0.0003 | -4.4611*** | 0.0061*** | 0.0006 | -0.0063*** |
| | (0.0010) | (0.0021) | (0.0023) | (0.0020) | (0.0015) | (0.0007) | (0.8379) | (0.0006) | (0.0019) | (0.0016) |
| Regosol | 0.0134*** | -0.0097*** | -0.0190*** | 0.0036 | -0.0012 | -0.0114*** | -0.0240** | 0.0069*** | -0.0013 | -0.0056*** |
| | (0.0019) | (0.0032) | (0.0020) | (0.0035) | (0.0021) | (0.0009) | (0.0100) | (0.0006) | (0.0018) | (0.0012) |
| Cambisol | 0.0207*** | -0.0136** | -0.0153*** | 0.0084*** | 0.0005 | 0.0041*** | -0.0136*** | 0.0001 | -0.0066** | 0.0020* |
| | (0.0020) | (0.0054) | (0.0025) | (0.0020) | (0.0020) | (0.0010) | (0.0029) | (0.0008) | (0.0033) | (0.0012) |
| Constant | -55.2384*** | -12.213*** | -55.9634*** | -39.249*** | 10.8876*** | 0.8999 | -670.4621*** | -13.167*** | -8.9116*** | -64.2370*** |
| | (2.8282) | (4.2312) | (3.6228) | (4.5598) | (2.0996) | (0.5685) | (155.3279) | (0.6674) | (2.0049) | (2.6270) |
| Observations | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 |

Robust standard errors in parentheses (clusters at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: maize. SD: Standard Deviation.

# Table 3.17 Multinomial Logit model 31 alternatives (2-2014)

| VARIABLES | cotton | grape | gretom | lemon | mango | melon | oat | onion | oranges | pigs |
|---|---|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | | | |
| Temperature | 3.8190*** | 2.4517*** | 0.3031* | 1.4201*** | 1.8377*** | -1.7190** | 1.5384*** | 2.6781*** | 7.0217*** | -0.2601 |
| | (0.7433) | (0.5358) | (0.1758) | (0.4172) | (0.5529) | (0.7045) | (0.2999) | (0.4737) | (0.6133) | (0.6385) |
| Temperature sq. | -0.1042*** | -0.0609*** | -0.0089* | 0.0044 | -0.0184* | 0.0351* | -0.0377*** | -0.0688*** | -0.1409*** | 0.0083 |
| | (0.0132) | (0.0126) | (0.0046) | (0.0074) | (0.0098) | (0.0208) | (0.0060) | (0.0117) | (0.0139) | (0.0122) |
| Rainfall | -4.6508 | 2.3102 | -0.3338* | 2.9838*** | 1.5446*** | -5.3693*** | 2.7244*** | -1.3189*** | 0.9571*** | 0.2841 |
| | (3.5616) | (1.7254) | (0.1855) | (0.2677) | (0.5423) | (1.3844) | (0.5074) | (0.3868) | (0.1905) | (0.6234) |
| Rainfall sq. | -0.2397 | -0.3455*** | -0.0025 | -0.0214*** | -0.0178** | -0.0412 | -0.0273* | 0.0009 | -0.0236*** | -0.0116 |
| | (0.2599) | (0.1279) | (0.0032) | (0.0038) | (0.0071) | (0.0642) | (0.0162) | (0.0081) | (0.0025) | (0.0104) |
| Temp.*Rainfall | 0.2042* | -0.0748 | 0.0168** | -0.1074*** | -0.0389** | 0.1998** | -0.1671*** | 0.0475** | -0.0189** | -0.0032 |
| | (0.1196) | (0.0559) | (0.0080) | (0.0091) | (0.0163) | (0.0776) | (0.0198) | (0.0193) | (0.0075) | (0.0202) |
| Temperature SD | 0.1520*** | 0.0153 | 0.0253** | -0.0392** | -0.0352*** | -0.0058 | 0.0433*** | 0.0192 | 0.0712*** | -0.0262 |
| | (0.0108) | (0.0099) | (0.0102) | (0.0164) | (0.0107) | (0.0110) | (0.0132) | (0.0140) | (0.0066) | (0.0285) |
| Rainfall seasonality | -0.0225** | 0.0061 | 0.0248*** | -0.0710*** | 0.0851*** | -0.0193* | 0.0059 | -0.0224*** | -0.0784*** | -0.0040 |
| | (0.0088) | (0.0092) | (0.0077) | (0.0054) | (0.0061) | (0.0103) | (0.0073) | (0.0072) | (0.0029) | (0.0051) |
| **Output prices** | | | | | | | | | | |
| Price cotton | 0.0168** | | | | | | | | | |
| | (0.0072) | | | | | | | | | |
| Price grape | | -0.0074*** | | | | | | | | |
| | | (0.0024) | | | | | | | | |
| Price gretom | | | -0.0090*** | | | | | | | |
| | | | (0.0031) | | | | | | | |
| Price lemon | | | | 0.0008 | | | | | | |
| | | | | (0.0008) | | | | | | |
| Price mango | | | | | -0.0059*** | | | | | |
| | | | | | (0.0019) | | | | | |
| Price melon | | | | | | -0.0015 | | | | |
| | | | | | | (0.0061) | | | | |
| Price oat | | | | | | | 0.0018 | | | |
| | | | | | | | (0.0015) | | | |
| Price onion | | | | | | | | -0.0007 | | |
| | | | | | | | | (0.0036) | | |
| Price oranges | | | | | | | | | -0.0039*** | |
| | | | | | | | | | (0.0007) | |
| Price pigs | | | | | | | | | | -0.0233*** |
| | | | | | | | | | | (0.0070) |
| **Inputs** | | | | | | | | | | |
| Wage rate | -0.0203*** | -0.0110* | 0.0118*** | 0.0082** | 0.0092*** | 0.0183*** | -0.0008 | 0.0071 | -0.0395*** | -0.0036 |
| | (0.0070) | (0.0061) | (0.0042) | (0.0036) | (0.0035) | (0.0068) | (0.0038) | (0.0072) | (0.0034) | (0.0081) |
| Plot size | 0.0509** | 0.1164 | -0.0272 | -0.0057 | 0.0022 | -0.0680 | -0.0537 | 0.0851 | -0.0264 | 0.0752 |
| | (0.0258) | (0.1667) | (0.0429) | (0.0363) | (0.0365) | (0.0444) | (0.0356) | (0.0797) | (0.0205) | (0.0532) |
| **Socio-demographic characteristics** | | | | | | | | | | |
| Age | 0.0074 | 0.0263*** | -0.0029 | -0.0009 | 0.0382*** | -0.0241** | 0.0046* | 0.0001 | 0.0261*** | 0.0121** |
| | (0.0133) | (0.0076) | (0.0047) | (0.0050) | (0.0092) | (0.0122) | (0.0024) | (0.0085) | (0.0032) | (0.0059) |
| Indigenous | -0.6844 | -1.5221** | -0.1687 | -0.6751*** | 0.1398 | -2.2410*** | -0.4574*** | -0.8646** | 0.2449*** | -0.2437 |
| | (0.4420) | (0.6695) | (0.1993) | (0.1633) | (0.1522) | (0.6777) | (0.1104) | (0.3645) | (0.0887) | (0.1976) |
| Schooling | 0.0133 | 0.0306 | 0.0531*** | -0.0108 | 0.1093*** | -0.0519 | 0.0299** | 0.0159 | 0.0838*** | 0.0379 |
| | (0.0278) | (0.0289) | (0.0206) | (0.0165) | (0.0264) | (0.0623) | (0.0145) | (0.0314) | (0.0103) | (0.0244) |
| **Access to markets** | | | | | | | | | | |
| Mobile | 1.1270*** | 0.0441 | 0.1027 | 0.5479*** | 0.4172*** | -0.0206 | 0.3787*** | 0.0452 | -0.2574** | 0.8186*** |
| | (0.2889) | (0.2759) | (0.1742) | (0.1333) | (0.1420) | (0.2816) | (0.0961) | (0.5630) | (0.1066) | (0.1905) |
| Internet | -0.5686* | 0.7511** | 0.3849* | 0.6463* | 0.4776 | -0.6614* | -0.2557 | 1.0087*** | -0.1946 | 1.9869*** |
| | (0.3137) | (0.3817) | (0.2124) | (0.3391) | (0.3051) | (0.3891) | (0.2951) | (0.2769) | (0.1828) | (0.3666) |
| City | 0.0053 | -0.0341*** | -0.0111 | -0.0870*** | -0.0208* | 0.0366*** | -0.0084** | -0.0332** | -0.0957*** | -0.0365** |
| | (0.0051) | (0.0097) | (0.0097) | (0.0091) | (0.0106) | (0.0091) | (0.0042) | (0.0143) | (0.0071) | (0.0174) |
| Road density | -1.5342 | -2.0842 | -0.0201 | 1.7415*** | -2.1193*** | -0.6706 | -1.4777*** | 0.6323 | 2.0392*** | -1.0677 |
| | (1.0885) | (1.3227) | (0.3452) | (0.2592) | (0.5142) | (1.5371) | (0.3007) | (0.3976) | (0.1710) | (0.7079) |
| **Soils** | | | | | | | | | | |
| Vertisol | -0.0086** | -0.0386** | 0.0011 | 0.0145*** | -0.0089*** | -0.0360*** | 0.0116*** | 0.0282*** | 0.0094*** | -0.0109*** |
| | (0.0038) | (0.0187) | (0.0028) | (0.0029) | (0.0033) | (0.0127) | (0.0012) | (0.0044) | (0.0011) | (0.0020) |
| Feozem | 0.0136*** | 0.0018 | 0.0066*** | 0.0220*** | -0.0051** | -0.0103 | 0.0054*** | 0.0244*** | 0.0181*** | -0.0045 |
| | (0.0041) | (0.0051) | (0.0023) | (0.0027) | (0.0024) | (0.0069) | (0.0009) | (0.0046) | (0.0017) | (0.0048) |
| Regosol | 0.0045* | 0.0223*** | 0.0172*** | -0.0103*** | -0.0245*** | -0.0011 | -0.0068*** | 0.0412*** | 0.0020 | -0.0130*** |
| | (0.0025) | (0.0047) | (0.0021) | (0.0040) | (0.0026) | (0.0029) | (0.0016) | (0.0044) | (0.0015) | (0.0044) |
| Cambisol | 0.0459*** | -62.8642*** | 0.0042 | 0.0025 | -0.0265*** | -0.0118** | -0.0022* | -0.0021 | 0.0150*** | -0.0273*** |
| | (0.0073) | (2.6970) | (0.0031) | (0.0045) | (0.0032) | (0.0060) | (0.0013) | (0.0133) | (0.0018) | (0.0072) |
| Constant | -42.2852*** | -28.3487*** | -10.154*** | -36.204*** | -49.8252*** | 23.0547*** | -18.890*** | -29.4947*** | -88.3153*** | -0.6520 |
| | (11.7833) | (6.7156) | (1.8297) | (6.0898) | (8.3742) | (5.7591) | (3.6728) | (5.3458) | (6.6179) | (11.2557) |
| Observations | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 |

Robust standard errors in parentheses (clusters at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: maize. SD: Standard Deviation.

# Table 3.18 Multinomial Logit model 31 alternatives (3-2014)

| VARIABLES | potato | poultry | redtom | rice | sorghum | soy | squash | sugarc | waterm | wheat |
|---|---|---|---|---|---|---|---|---|---|---|
| **Climate** | | | | | | | | | | |
| Temperature | -1.4124*** | 0.7550 | 1.9287*** | 1.7971** | 4.4238*** | 20.1884*** | -0.1388 | 5.3547*** | 3.0508*** | -0.3725** |
| | (0.3433) | (0.4634) | (0.3315) | (0.7424) | (0.2288) | (3.2670) | (0.1692) | (0.3114) | (0.6358) | (0.1448) |
| Temperature sq. | 0.0459*** | -0.0180 | -0.0406*** | -0.0221 | -0.1085*** | -0.4751*** | 0.0072* | -0.1152*** | -0.0777*** | 0.0330*** |
| | (0.0073) | (0.0116) | (0.0086) | (0.0142) | (0.0060) | (0.0751) | (0.0042) | (0.0078) | (0.0170) | (0.0029) |
| Rainfall | 1.3496*** | 0.0681 | -0.3036 | 2.3586*** | -0.9148*** | -8.2795*** | -0.2184 | 0.2453** | -2.0708** | 3.3894*** |
| | (0.2368) | (0.1629) | (0.2955) | (0.5635) | (0.1863) | (2.0244) | (0.1590) | (0.1139) | (0.9255) | (0.3105) |
| Rainfall sq. | 0.0160*** | -0.0107** | 0.0160*** | -0.0525*** | -0.0730*** | -0.2558*** | 0.0040 | -0.0193*** | -0.0126* | -0.0692*** |
| | (0.0049) | (0.0051) | (0.0025) | (0.0088) | (0.0052) | (0.0309) | (0.0038) | (0.0046) | (0.0069) | (0.0116) |
| Temp.*Rainfall | -0.0954*** | 0.0125 | -0.0158 | -0.0397** | 0.0808*** | 0.5130*** | -0.0014 | 0.0179* | 0.0982** | -0.1638*** |
| | (0.0104) | (0.0087) | (0.0126) | (0.0189) | (0.0084) | (0.0783) | (0.0097) | (0.0092) | (0.0410) | (0.0116) |
| Temperature SD | -0.0269* | 0.0201 | -0.0747*** | -0.0543*** | 0.0455*** | 0.0688*** | 0.0020 | 0.0184* | 0.0530*** | 0.0660*** |
| | (0.0150) | (0.0258) | (0.0129) | (0.0178) | (0.0031) | (0.0104) | (0.0076) | (0.0101) | (0.0143) | (0.0055) |
| Rainfall seasonality | -0.0393*** | -0.0034 | 0.0036 | 0.0594*** | -0.0087*** | -0.0036 | 0.0033 | 0.0101** | 0.0311*** | -0.0370*** |
| | (0.0065) | (0.0076) | (0.0054) | (0.0069) | (0.0017) | (0.0048) | (0.0055) | (0.0049) | (0.0075) | (0.0025) |
| **Output prices** | | | | | | | | | | |
| Price potato | 0.0112*** | | | | | | | | | |
| | (0.0025) | | | | | | | | | |
| Price poultry | | 0.0214* | | | | | | | | |
| | | (0.0128) | | | | | | | | |
| Price redtom | | | 0.0030 | | | | | | | |
| | | | (0.0020) | | | | | | | |
| Price rice | | | | 0.0260** | | | | | | |
| | | | | (0.0102) | | | | | | |
| Price sorghum | | | | | 0.0009 | | | | | |
| | | | | | (0.0011) | | | | | |
| Price soy | | | | | | 0.0037 | | | | |
| | | | | | | (0.0047) | | | | |
| Price squash | | | | | | | -0.0007 | | | |
| | | | | | | | (0.0019) | | | |
| Price sugarc | | | | | | | | 0.0129*** | | |
| | | | | | | | | (0.0011) | | |
| Price waterm | | | | | | | | | 0.0017 | |
| | | | | | | | | | (0.0027) | |
| Price wheat | | | | | | | | | | -0.0059*** |
| | | | | | | | | | | (0.0018) |
| **Inputs** | | | | | | | | | | |
| Wage rate | -0.0147** | -0.0158** | -0.0324*** | 0.0254*** | 0.0060*** | 0.0261*** | -0.0082 | 0.0022 | -0.0027 | -0.0431*** |
| | (0.0067) | (0.0067) | (0.0090) | (0.0031) | (0.0018) | (0.0031) | (0.0086) | (0.0021) | (0.0084) | (0.0038) |
| Plot size | 0.3495*** | 0.1051 | -0.0244 | 0.2645*** | 0.0776*** | 0.2815*** | -0.0605 | 0.0516*** | 0.0047 | 0.1019*** |
| | (0.0570) | (0.0916) | (0.0518) | (0.0565) | (0.0160) | (0.0491) | (0.0388) | (0.0172) | (0.0666) | (0.0192) |
| **Socio-demographic characteristics** | | | | | | | | | | |
| Age | 0.0041 | 0.0230* | -0.0107* | 0.0145 | 0.0087*** | -0.0195*** | -0.0225*** | 0.0210*** | -0.0111 | 0.0105*** |
| | (0.0095) | (0.0131) | (0.0058) | (0.0113) | (0.0019) | (0.0061) | (0.0045) | (0.0036) | (0.0091) | (0.0032) |
| Indigenous | -1.2924*** | -0.3656 | 0.3391* | -0.9137*** | -0.9086*** | -1.3849*** | 0.2439* | -0.6700*** | -0.2623 | -0.0779 |
| | (0.3814) | (0.3427) | (0.1792) | (0.3121) | (0.1256) | (0.3034) | (0.1427) | (0.0836) | (0.2876) | (0.1257) |
| Schooling | -0.0178 | 0.0459 | 0.0141 | 0.0865** | 0.0397*** | -0.0091 | -0.0306* | 0.0594*** | 0.0509* | 0.0560*** |
| | (0.0229) | (0.0347) | (0.0223) | (0.0363) | (0.0073) | (0.0230) | (0.0181) | (0.0213) | (0.0264) | (0.0099) |
| **Access to markets** | | | | | | | | | | |
| Mobile | 0.2976 | 0.0331 | 0.9683*** | 1.5909*** | 0.2454*** | 0.9912*** | -0.3041* | 0.4948*** | 1.2391*** | 0.6781*** |
| | (0.2652) | (0.2775) | (0.3080) | (0.2948) | (0.0595) | (0.1691) | (0.1592) | (0.0847) | (0.2441) | (0.1035) |
| Internet | 2.1129*** | 1.8874*** | 1.6284*** | -0.1318 | -0.7838*** | 0.6113** | 1.1600*** | 0.3494 | -0.0896 | -0.4927*** |
| | (0.2991) | (0.4555) | (0.3235) | (0.4480) | (0.1182) | (0.2535) | (0.2082) | (0.3616) | (0.3928) | (0.1238) |
| City | 0.0069 | -0.0014 | 0.0113 | 0.0340 | -0.0021 | 0.0187*** | 0.0084 | -0.0849*** | -0.0018 | -0.0224*** |
| | (0.0108) | (0.0218) | (0.0146) | (0.0559) | (0.0029) | (0.0064) | (0.0104) | (0.0085) | (0.0144) | (0.0044) |
| Road density | -1.1394 | 1.0534* | -1.8056*** | 1.7939** | 0.4215** | 2.0956*** | -0.3913 | -0.0127 | -1.9422* | 1.3112*** |
| | (0.7131) | (0.5509) | (0.5122) | (0.7389) | (0.1664) | (0.5314) | (0.4322) | (0.1699) | (1.1737) | (0.1963) |
| **Soils** | | | | | | | | | | |
| Vertisol | 0.0231*** | -0.0143*** | 0.0003 | 0.0036 | 0.0102*** | 0.0134*** | 0.0000 | -0.0025 | -0.0405*** | 0.0153*** |
| | (0.0025) | (0.0037) | (0.0028) | (0.0029) | (0.0007) | (0.0023) | (0.0034) | (0.0030) | (0.0082) | (0.0014) |
| Feozem | -0.0201*** | -0.0051 | 0.0117*** | -0.0071 | 0.0043*** | 0.0054 | -0.0010 | -0.0023 | 0.0004 | 0.0176*** |
| | (0.0057) | (0.0042) | (0.0026) | (0.0046) | (0.0009) | (0.0043) | (0.0023) | (0.0024) | (0.0042) | (0.0015) |
| Regosol | -0.0134** | -0.0048 | 0.0118*** | -0.0205*** | -0.0031*** | -0.0066 | 0.0038 | -0.0137*** | 0.0074** | 0.0096*** |
| | (0.0061) | (0.0035) | (0.0027) | (0.0045) | (0.0012) | (0.0046) | (0.0025) | (0.0020) | (0.0034) | (0.0014) |
| Cambisol | 0.0004 | -0.0008 | 0.0095** | -0.0195*** | 0.0111*** | -0.0820*** | -0.0071* | -0.0259*** | 0.0017 | 0.0196*** |
| | (0.0062) | (0.0087) | (0.0047) | (0.0042) | (0.0013) | (0.0267) | (0.0037) | (0.0036) | (0.0050) | (0.0017) |
| Constant | 7.4132* | -20.4604*** | -21.6793*** | -55.9148*** | -49.6107*** | -233.498*** | -2.2418 | -71.4836*** | -39.1462*** | -7.0160*** |
| | (3.9291) | (5.4273) | (2.8466) | (9.7617) | (2.1314) | (34.5493) | (2.1091) | (3.3640) | (5.7743) | (2.0031) |
| Observations | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 | 168,265 |

Robust standard errors in parentheses (clusters at the farm level)
*** p<0.01, ** p<0.05, * p<0.1
Base category: maize. SD: Standard Deviation.

## Table 3.19 Nested Logit model 31 alternatives (1-2012)

| | Beverage | | Cereals | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **cacao** | **coffee** | **barley** | **maize** | **oat** | **rice** | **sorghum** | **wheat** | **Middle choice** | **ASC** |
| **Inclusive values** | | | | | | | | | | |
| IV beverage | | | | | | | | | 0.5843*** | -3.4392*** |
| | | | | | | | | | (0.0126) | (0.0408) |
| IV cereals | | | | | | | | | 0.0262*** | |
| | | | | | | | | | (0.0019) | |
| IV fruits | | | | | | | | | 0.0779*** | -3.2404*** |
| | | | | | | | | | (0.0021) | (0.0554) |
| IV livestock | | | | | | | | | 0.5653*** | -3.8653*** |
| | | | | | | | | | (0.0108) | (0.0800) |
| IV other | | | | | | | | | 0.0177* | -0.6879*** |
| | | | | | | | | | (0.0092) | (0.0505) |
| IV vegetables | | | | | | | | | 0.1769*** | -3.0693*** |
| | | | | | | | | | (0.0407) | (0.0731) |
| **Climate** | | | | | | | | | | |
| Temperature | 10.5397 | | -7.5682*** | -5.7384*** | -3.2297*** | | -1.0008 | -1.8535* | | |
| | (8.4040) | | (0.8623) | (0.8471) | (0.8771) | | (0.8760) | (0.9532) | | |
| Temperature sq. | -0.1425 | | 0.1283*** | 0.0856*** | 0.0207 | | -0.0447*** | 0.0390** | | |
| | (0.1592) | | (0.0151) | (0.0147) | (0.0157) | | (0.0160) | (0.0169) | | |
| Rainfall | 2.1209** | | -2.9555*** | -4.8521*** | -2.0818*** | | -7.5701*** | 5.8860*** | | |
| | (0.9830) | | (0.9608) | (0.5800) | (0.6500) | | (0.6137) | (1.0626) | | |
| Rainfall sq. | -0.0075 | | -0.1254** | 0.0649*** | 0.0389*** | | -0.0279** | -0.2426*** | | |
| | (0.0051) | | (0.0536) | (0.0097) | (0.0138) | | (0.0111) | (0.0341) | | |
| Temp.*Rainfall | -0.0722** | | 0.1092*** | 0.1303*** | -0.0463** | | 0.3097*** | -0.3214*** | | |
| | (0.0299) | | (0.0249) | (0.0186) | (0.0225) | | (0.0209) | (0.0386) | | |
| Temperature SD | 0.0426 | | -0.0351* | 0.0123 | 0.0146 | | 0.0889*** | 0.0822*** | | |
| | (0.0400) | | (0.0201) | (0.0164) | (0.0171) | | (0.0167) | (0.0180) | | |
| Rainfall seasonality | -0.0809*** | | -0.1207*** | -0.0513*** | -0.0418*** | | -0.0574*** | -0.0693*** | | |
| | (0.0171) | | (0.0121) | (0.0080) | (0.0090) | | (0.0081) | (0.0089) | | |
| **Output prices** | | | | | | | | | | |
| Price cacao | 0.0456** | | | | | | | | | |
| | (0.0192) | | | | | | | | | |
| Price barley | | | 0.0073** | | | | | | | |
| | | | (0.0033) | | | | | | | |
| Price maize | | | | 0.0181*** | | | | | | |
| | | | | (0.0011) | | | | | | |
| Price oat | | | | | -0.0036*** | | | | | |
| | | | | | (0.0011) | | | | | |
| Price sorghum | | | | | | | 0.0097*** | | | |
| | | | | | | | (0.0008) | | | |
| Price wheat | | | | | | | | -0.0283*** | | |
| | | | | | | | | (0.0025) | | |
| **Inputs** | | | | | | | | | | |
| Wage rate | -0.0167 | | -0.0043* | -0.0052** | -0.0038 | | -0.0083*** | -0.0090*** | | |
| | (0.0115) | | (0.0026) | (0.0023) | (0.0025) | | (0.0026) | (0.0032) | | |
| Plot size | 0.0458 | | -0.2054*** | -0.4032*** | -0.3459*** | | -0.3827*** | -0.1501*** | | |
| | (0.1107) | | (0.0513) | (0.0453) | (0.0484) | | (0.0471) | (0.0533) | | |
| **Socio-demographic characteristics** | | | | | | | | | | |
| Age | 0.0104 | | 0.0090 | -0.0027 | -0.0006 | | 0.0023 | 0.0009 | | |
| | (0.0129) | | (0.0070) | (0.0064) | (0.0068) | | (0.0067) | (0.0074) | | |
| Indigenous | -2.4101*** | | -0.5149 | 1.5509*** | 1.0702** | | -1.5324*** | 1.1085* | | |
| | (0.7199) | | (0.5934) | (0.4820) | (0.4973) | | (0.5463) | (0.5738) | | |
| Schooling | -0.0192 | | 0.0136 | -0.0383** | 0.0136 | | -0.0375* | -0.0456** | | |
| | (0.0391) | | (0.0217) | (0.0189) | (0.0203) | | (0.0195) | (0.0228) | | |
| **Access to markets** | | | | | | | | | | |
| Mobile | 0.5455* | | -0.3653 | -0.9205*** | -0.6558*** | | -0.5028** | -0.4664* | | |
| | (0.3096) | | (0.2454) | (0.2236) | (0.2334) | | (0.2264) | (0.2511) | | |
| Internet | -1.7475*** | | 1.5395** | 1.1822* | 0.6605 | | 0.9646 | 0.8248 | | |
| | (0.6598) | | (0.7002) | (0.6686) | (0.6831) | | (0.6692) | (0.6808) | | |
| City | -0.0440 | | 0.0362* | 0.0531*** | 0.0582*** | | 0.0526*** | 0.0362** | | |
| | (0.0487) | | (0.0200) | (0.0171) | (0.0173) | | (0.0173) | (0.0181) | | |
| Road density | 2.9520*** | | -3.8214*** | -3.1492*** | -4.7857*** | | -2.0093*** | -2.6609*** | | |
| | (0.7216) | | (0.5634) | (0.5419) | (0.5531) | | (0.5443) | (0.5722) | | |
| **Soils** | | | | | | | | | | |
| Vertisol | 0.0060 | | 0.0005 | -0.0053** | 0.0029 | | 0.0086*** | 0.0107*** | | |
| | (0.0053) | | (0.0032) | (0.0023) | (0.0025) | | (0.0024) | (0.0027) | | |
| Feozem | -2.6986*** | | 0.0246*** | 0.0068 | 0.0097** | | 0.0140*** | 0.0308*** | | |
| | (0.5388) | | (0.0049) | (0.0047) | (0.0048) | | (0.0048) | (0.0050) | | |
| Regosol | -0.0212 | | 0.0337*** | 0.0285*** | 0.0253*** | | 0.0275*** | 0.0506*** | | |
| | (0.0194) | | (0.0033) | (0.0028) | (0.0032) | | (0.0030) | (0.0036) | | |
| Cambisol | 0.0089 | | 0.0214*** | 0.0154*** | 0.0102*** | | 0.0301*** | 0.0452*** | | |
| | (0.0059) | | (0.0038) | (0.0035) | (0.0039) | | (0.0035) | (0.0038) | | |
| Constant | -181.3728 | | 125.1538*** | 105.5919*** | 83.4497*** | | 58.6021*** | 47.3133*** | | |
| | (111.7049) | | (12.6293) | (12.2833) | (12.5350) | | (12.4304) | (13.5671) | | |
| Observations | 6,634 | | 713,082 | 713,082 | 713,082 | | 713,083 | 713,084 | 1,319,910 | 1,319,910 |

Top: robust standard errors in parentheses (using bootstrap and clusters at the farm level, 1000 reps.)
Bottom: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

# Table 3.20 Nested Logit model 31 alternatives (2-2012)

| | | | | Fruits | | | | | Livestock | |
|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **apples** | **avocado** | **bananas** | **grape** | **lemon** | **mango** | **oranges** | **cattle** | **pigs** | **poultry** |
| | | | | | **Climate** | | | | | |
| Temperature | | 4.1985 | 7.4893** | 13.5826** | 6.3186* | 3.5223 | 3.7350 | 0.7957** | | 3.0708*** |
| | | (2.7577) | (3.6383) | (5.4317) | (3.3790) | (3.5844) | (3.5296) | (0.3670) | | (0.6235) |
| Temperature sq. | | -0.0620 | -0.0847 | -0.2688** | -0.0720 | -0.0352 | -0.0325 | -0.0242*** | | -0.0769*** |
| | | (0.0831) | (0.0991) | (0.1305) | (0.0951) | (0.0992) | (0.0976) | (0.0079) | | (0.0146) |
| Rainfall | | 2.3026*** | 4.1247*** | 23.8451*** | 3.0161*** | -0.4215 | 1.7258 | -0.2985 | | -0.5568* |
| | | (0.8711) | (1.0778) | (8.0090) | (1.0354) | (1.1132) | (1.0723) | (0.2440) | | (0.3305) |
| Rainfall sq. | | -0.0627** | -0.0440* | -1.6050*** | -0.0378 | -0.0745*** | -0.0478* | -0.0132*** | | -0.0026 |
| | | (0.0291) | (0.0256) | (0.4776) | (0.0256) | (0.0261) | (0.0257) | (0.0037) | | (0.0043) |
| Temp.*Rainfall | | -0.0339 | -0.1212* | -0.7514*** | -0.0948 | 0.0848 | -0.0283 | 0.0350*** | | 0.0260* |
| | | (0.0593) | (0.0682) | (0.2888) | (0.0672) | (0.0699) | (0.0691) | (0.0101) | | (0.0152) |
| Temperature SD | | -0.5576*** | -0.4915*** | -0.0363 | -0.4519*** | -0.3220** | -0.2418* | 0.0298** | | -0.0328* |
| | | (0.1204) | (0.1327) | (0.0703) | (0.1316) | (0.1308) | (0.1319) | (0.0127) | | (0.0169) |
| Rainfall seasonality | | 0.0254 | -0.0250 | -0.0661** | -0.0453 | 0.0869* | -0.0872* | -0.0070 | | -0.0186** |
| | | (0.0508) | (0.0468) | (0.0293) | (0.0463) | (0.0467) | (0.0458) | (0.0066) | | (0.0091) |
| | | | | | **Output prices** | | | | | |
| Price avocado | | -0.0026 | | | | | | | | |
| | | (0.0032) | | | | | | | | |
| Price bananas | | | 0.0097*** | | | | | | | |
| | | | (0.0026) | | | | | | | |
| Price grape | | | | -0.0225*** | | | | | | |
| | | | | (0.0075) | | | | | | |
| Price lemon | | | | | 0.0060*** | | | | | |
| | | | | | (0.0012) | | | | | |
| Price mango | | | | | | -0.0281*** | | | | |
| | | | | | | (0.0031) | | | | |
| Price oranges | | | | | | | 0.0037* | | | |
| | | | | | | | (0.0020) | | | |
| Price cattle | | | | | | | | 0.0003 | | |
| | | | | | | | | (0.0083) | | |
| Price pigs | | | | | | | | | | 0.0108 |
| | | | | | | | | | | (0.0067) |
| | | | | | **Inputs** | | | | | |
| Wage rate | | 0.0080 | 0.0129 | 0.0469*** | -0.0156 | -0.0089 | -0.0099 | -0.0063** | | -0.0032 |
| | | (0.0119) | (0.0122) | (0.0163) | (0.0126) | (0.0125) | (0.0123) | (0.0031) | | (0.0038) |
| Plot size | | 0.3436 | 0.1542 | -0.0678 | 0.2345 | 0.1440 | 0.2213 | 0.3246*** | | 0.0675 |
| | | (0.2201) | (0.2191) | (0.2155) | (0.2182) | (0.2193) | (0.2148) | (0.0299) | | (0.0431) |
| | | | | | **Socio-demographic characteristics** | | | | | |
| Age | | 0.0027 | -0.0146 | -0.0348** | -0.0155 | 0.0008 | -0.0313** | 0.0004 | | -0.0291*** |
| | | (0.0155) | (0.0160) | (0.0145) | (0.0159) | (0.0158) | (0.0149) | (0.0087) | | (0.0111) |
| Indigenous | | -1.0032 | 0.5860 | -5.3743 | 0.1073 | 0.6965 | 1.7428 | -0.4259 | | -2.6825** |
| | | (0.9536) | (1.3503) | (6.0908) | (1.3371) | (1.3731) | (1.3250) | (0.3839) | | (1.0942) |
| Schooling | | -0.1010* | -0.0976* | -0.1682*** | -0.1015** | -0.0636 | -0.1635*** | -0.1096*** | | 0.0019 |
| | | (0.0517) | (0.0515) | (0.0484) | (0.0516) | (0.0510) | (0.0489) | (0.0223) | | (0.0364) |
| | | | | | **Access to markets** | | | | | |
| Mobile | | 0.2223 | 0.4214 | -0.3060 | -0.0475 | -0.4817 | -0.0511 | -0.3080 | | 0.4150 |
| | | (0.4512) | (0.4837) | (0.5382) | (0.4727) | (0.4686) | (0.4632) | (0.2153) | | (0.3667) |
| Internet | | 0.0303 | 1.0314 | 1.8571** | 0.7642 | 0.3925 | 1.1931* | -2.0054*** | | -0.6132* |
| | | (0.7288) | (0.7332) | (0.7389) | (0.7072) | (0.7109) | (0.6731) | (0.2208) | | (0.3260) |
| City | | 0.0356 | -0.0084 | -0.0120 | 0.0214 | 0.0507 | 0.0142 | 0.0351** | | -0.0205 |
| | | (0.0589) | (0.0592) | (0.0498) | (0.0569) | (0.0574) | (0.0560) | (0.0143) | | (0.0219) |
| Road density | | -7.1756** | -5.6234** | 2.4801 | -7.7862*** | -8.3065*** | -6.2538** | -0.5500 | | 0.8113 |
| | | (2.9913) | (2.7009) | (1.9089) | (2.7408) | (2.7673) | (2.6710) | (0.5084) | | (0.5856) |
| | | | | | **Soils** | | | | | |
| Vertisol | | -0.0428*** | -0.0395*** | -0.0245** | -0.0272* | -0.0393*** | -0.0296** | 0.0060** | | 0.0070* |
| | | (0.0138) | (0.0148) | (0.0122) | (0.0145) | (0.0144) | (0.0146) | (0.0030) | | (0.0037) |
| Feozem | | -0.0164* | -0.0041 | 0.0032 | -0.0000 | -0.0133 | 0.0042 | 0.0028 | | 0.0100*** |
| | | (0.0093) | (0.0104) | (0.0091) | (0.0101) | (0.0101) | (0.0103) | (0.0028) | | (0.0033) |
| Regosol | | 0.0199 | 0.0258 | 0.0157 | 0.0282 | 0.0167 | 0.0313 | 0.0134*** | | -0.0014 |
| | | (0.0195) | (0.0196) | (0.0107) | (0.0195) | (0.0196) | (0.0196) | (0.0036) | | (0.0046) |
| Cambisol | | -0.0254** | -0.0292** | 0.0000 | -0.0227** | -0.0320*** | -0.0478*** | 0.0150*** | | 0.0151** |
| | | (0.0104) | (0.0116) | (0.0000) | (0.0113) | (0.0114) | (0.0130) | (0.0049) | | (0.0071) |
| Constant | | -44.8164* | -106.5312*** | -157.8573*** | -77.4962** | -49.1114 | -41.4345 | -2.8583 | | -27.2084*** |
| | | (23.0204) | (35.2539) | (60.2120) | (30.7223) | (33.3335) | (32.3238) | (4.6466) | | (7.2846) |
| | | 61,887 | 61,887 | 61,887 | 61,887 | 61,887 | 61,887 | 123,264 | | 123,264 |

Top: robust standard errors in parentheses (using bootstrap and clusters at the farm level, 1000 reps.)
Bottom: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

# Table 3.21 Nested Logit model 31 alternatives (3-2012)

| | | | | Other | | | | | | Vegetables | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **alfalfa** | **beans** | **chilli** | **cotton** | **potato** | **soy** | **sugarc** | **gretom** | **melon** | **onion** | **redtom** | **squash** | **waterm** |
| | | | | | | | **Climate** | | | | | | |
| Temperature | 6.8140*** | | 2.5954*** | 3.0135*** | -0.5762 | 17.9616*** | 7.3639*** | -0.5393 | -1.3964 | 2.0784*** | | -1.3391*** | 1.2658 |
| | (0.3952) | | (0.3379) | (0.8005) | (0.8602) | (5.8094) | (0.4591) | (0.3763) | (0.8900) | (0.5546) | | (0.3271) | (0.9906) |
| Temp. sq. | -0.1470*** | | -0.0677*** | -0.0759*** | 0.0432*** | -0.4048*** | -0.1439*** | -0.0018 | 0.0144 | -0.0490*** | | 0.0316*** | -0.0460* |
| | (0.0090) | | (0.0090) | (0.0193) | (0.0165) | (0.1403) | (0.0121) | (0.0094) | (0.0238) | (0.0142) | | (0.0082) | (0.0241) |
| Rainfall | 4.3820*** | | -2.4471*** | -6.0258*** | 5.3090*** | -7.6424** | 2.9950*** | -0.4638 | -9.8478*** | -0.1507 | | 0.2185 | -7.229*** |
| | (0.4093) | | (0.4452) | (1.5851) | (1.4814) | (2.9737) | (0.4070) | (0.3101) | (1.7965) | (0.3902) | | (0.2782) | (1.5614) |
| Rainfall sq. | -0.0257* | | -0.0455*** | 0.0055 | -0.0202 | -0.1195*** | -0.0101* | -0.025*** | -0.0370 | 0.0056 | | -0.0074 | -0.051*** |
| | (0.0154) | | (0.0167) | (0.0278) | (0.0539) | (0.0344) | (0.0056) | (0.0063) | (0.0252) | (0.0059) | | (0.0069) | (0.0135) |
| Temp.*Rainfall | -0.2063*** | | 0.1251*** | 0.2107*** | -0.237*** | 0.3785*** | -0.1047*** | 0.0525*** | 0.3961*** | 0.0014 | | -0.0035 | 0.3316*** |
| | (0.0165) | | (0.0247) | (0.0764) | (0.0442) | (0.1430) | (0.0206) | (0.0154) | (0.0827) | (0.0171) | | (0.0127) | (0.0698) |
| Temp. SD | 0.1114*** | | 0.0460*** | 0.2122*** | 0.0840*** | -0.0160 | -0.0706*** | -0.0070 | 0.0625** | 0.0060 | | 0.0468*** | 0.1336*** |
| | (0.0067) | | (0.0084) | (0.0133) | (0.0264) | (0.0129) | (0.0133) | (0.0194) | (0.0290) | (0.0184) | | (0.0131) | (0.0257) |
| Rainfall S. | -0.0997*** | | -0.0656*** | -0.1309*** | -0.125*** | -0.1300*** | -0.0784*** | -0.0033 | -0.0300** | -0.0525*** | | -0.0052 | 0.0029 |
| | (0.0059) | | (0.0046) | (0.0105) | (0.0208) | (0.0094) | (0.0057) | (0.0093) | (0.0135) | (0.0117) | | (0.0068) | (0.0117) |
| | | | | | | | **Output prices** | | | | | | |
| Price alfalfa | 0.0039*** | | | | | | | | | | | | |
| | (0.0012) | | | | | | | | | | | | |
| Price beans | | | | | | | | | | | | | |
| Price chilli | | | -0.0082*** | | | | | | | | | | |
| | | | (0.0017) | | | | | | | | | | |
| Price cotton | | | | -0.0225** | | | | | | | | | |
| | | | | (0.0088) | | | | | | | | | |
| Price potato | | | | | -0.0000 | | | | | | | | |
| | | | | | (0.0062) | | | | | | | | |
| Price soy | | | | | | -0.0253*** | | | | | | | |
| | | | | | | (0.0045) | | | | | | | |
| Price sugarc | | | | | | | 0.0310*** | | | | | | |
| | | | | | | | (0.0044) | | | | | | |
| Price gretom | | | | | | | | 0.0034 | | | | | |
| | | | | | | | | (0.0034) | | | | | |
| Price melon | | | | | | | | | 0.0067 | | | | |
| | | | | | | | | | (0.0069) | | | | |
| Price onion | | | | | | | | | | 0.0070** | | | |
| | | | | | | | | | | (0.0034) | | | |
| Price redtom | | | | | | | | | | | | | |
| Price squash | | | | | | | | | | | | 0.0005 | |
| | | | | | | | | | | | | (0.0042) | |
| Price waterm | | | | | | | | | | | | | -0.0029 |
| | | | | | | | | | | | | | (0.0032) |
| | | | | | | | **Inputs** | | | | | | |
| Wage rate | -0.0002 | | 0.0016 | -0.0468*** | 0.0149** | -0.0200*** | 0.0010 | -0.0091 | -0.0009 | 0.0149*** | | 0.0027 | 0.0034 |
| | (0.0020) | | (0.0026) | (0.0089) | (0.0059) | (0.0048) | (0.0042) | (0.0063) | (0.0082) | (0.0044) | | (0.0043) | (0.0090) |
| Plot size | 0.0312 | | 0.2115*** | 0.2782*** | 0.4271*** | 0.5859*** | 0.1946*** | 0.0186 | -0.2541** | -0.0301 | | -0.1879** | -0.242*** |
| | (0.0331) | | (0.0377) | (0.0644) | (0.1078) | (0.0738) | (0.0518) | (0.0685) | (0.1224) | (0.0631) | | (0.0771) | (0.0850) |
| | | | | | | | **Socio-demographic characteristics** | | | | | | |
| Age | 0.0178*** | | -0.0146*** | -0.0122 | 0.0380* | -0.0227** | -0.0068 | 0.0021 | 0.0014 | -0.0008 | | -0.0126 | 0.0104 |
| | (0.0037) | | (0.0038) | (0.0091) | (0.0203) | (0.0107) | (0.0113) | (0.0093) | (0.0099) | (0.0090) | | (0.0080) | (0.0162) |
| Indigenous | 0.6206*** | | -0.8923*** | -16.695*** | -1.6039** | -3.3183*** | -2.7559*** | 1.5837*** | -15.521*** | -1.5310* | | 1.4242*** | -1.9498** |
| | (0.2055) | | (0.3076) | (1.1206) | (0.7855) | (0.3397) | (0.3023) | (0.5445) | (0.7838) | (0.7947) | | (0.4854) | (0.8144) |
| Schooling | 0.0625*** | | 0.0043 | 0.0108 | 0.1721*** | -0.0121 | 0.0905*** | -0.0519** | -0.1377*** | -0.0733*** | | -0.0211 | -0.0808** |
| | (0.0121) | | (0.0121) | (0.0345) | (0.0372) | (0.0314) | (0.0191) | (0.0246) | (0.0330) | (0.0255) | | (0.0245) | (0.0314) |
| | | | | | | | **Access to markets** | | | | | | |
| Mobile | 0.4015*** | | 0.4054*** | 0.0639 | 0.7746* | 0.2837 | -0.6934*** | 0.1875 | -0.5150** | 0.4559* | | -0.6409*** | 0.0759 |
| | (0.0884) | | (0.0937) | (0.2387) | (0.4018) | (0.2796) | (0.1765) | (0.2486) | (0.2263) | (0.2456) | | (0.2045) | (0.2708) |
| Internet | 0.3742** | | 0.5332*** | -0.2641 | 1.5077*** | 1.8925*** | 1.5615*** | 0.7243** | -1.4540*** | 0.2021 | | -0.0743 | -1.154*** |
| | (0.1838) | | (0.2038) | (0.3106) | (0.3964) | (0.5959) | (0.5954) | (0.3506) | (0.5396) | (0.2919) | | (0.3073) | (0.4368) |
| City | -0.0219*** | | -0.0278*** | -0.0248*** | -0.0056 | 0.0447*** | -0.0620*** | -0.071*** | -0.0183 | -0.0919*** | | 0.0057 | -0.0211 |
| | (0.0058) | | (0.0070) | (0.0066) | (0.0185) | (0.0121) | (0.0124) | (0.0183) | (0.0145) | (0.0218) | | (0.0136) | (0.0144) |
| Road density | 5.1695*** | | 2.7544*** | 3.4139*** | 1.9988** | 4.2882*** | 1.8592*** | 0.6189 | 4.4368*** | 1.8475*** | | 0.7870 | -1.3465 |
| | (0.2683) | | (0.3659) | (0.8507) | (0.9122) | (0.5528) | (0.3522) | (0.4521) | (1.0679) | (0.5392) | | (0.6702) | (1.4458) |
| | | | | | | | **Soils** | | | | | | |
| Vertisol | 0.0070*** | | -0.0110*** | -0.0157*** | 0.0236*** | 0.0010 | -0.0045 | 0.0025 | -0.0444*** | 0.0183*** | | -0.0019 | -0.041*** |
| | (0.0014) | | (0.0025) | (0.0054) | (0.0045) | (0.0036) | (0.0030) | (0.0042) | (0.0100) | (0.0036) | | (0.0039) | (0.0067) |
| Feozem | 0.0063*** | | 0.0028* | -0.0106 | 0.0001 | 0.0138*** | -0.0006 | 0.0070* | -0.0186** | 0.0039 | | -0.0066** | -0.0100* |
| | (0.0012) | | (0.0015) | (0.0065) | (0.0049) | (0.0046) | (0.0020) | (0.0038) | (0.0074) | (0.0037) | | (0.0029) | (0.0052) |
| Regosol | 0.0170*** | | 0.0155*** | 0.0058 | 0.0043 | -0.0135*** | -0.0088*** | 0.0034 | -0.0064 | 0.0177*** | | -0.0087*** | -0.028*** |
| | (0.0017) | | (0.0021) | (0.0036) | (0.0078) | (0.0042) | (0.0022) | (0.0034) | (0.0042) | (0.0034) | | (0.0029) | (0.0048) |
| Cambisol | 0.0177*** | | -0.0098** | 0.0197* | 0.0030 | -0.1264*** | -0.0256*** | -0.0030 | -0.0014 | -0.0047 | | -0.0116** | -0.015*** |
| | (0.0028) | | (0.0041) | (0.0111) | (0.0090) | (0.0276) | (0.0030) | (0.0047) | (0.0080) | (0.0070) | | (0.0055) | (0.0053) |
| Constant | -75.837*** | | -19.853*** | -19.7155** | -10.6882 | -185.438*** | -88.945*** | 7.7476** | 27.2311*** | -19.2142*** | | 12.8687*** | -10.1859 |
| | (4.4683) | | (3.3387) | (9.4143) | (11.5735) | (60.9946) | (4.4430) | (3.7093) | (9.5558) | (5.5179) | | (3.3158) | (11.3416) |
| | 300,783 | | 300,783 | 300,783 | 300,783 | 300,783 | 300,783 | 29,538 | 29,538 | 29,538 | | 29,538 | 29,538 |

Top: robust standard errors in parentheses (using bootstrap and clusters at the farm level, 1000 reps.)
Bottom: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

## Table 3.22 Nested Logit model 31 alternatives (1-2014)

| | Beverage | | Cereals | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | cacao | coffee | barley | maize | oat | rice | sorghum | wheat | Middle choice | ASC |
| **Inclusive values** | | | | | | | | | | |
| IV beverage | | | | | | | | | 0.1961*** | -2.8091*** |
| | | | | | | | | | (0.0065) | (0.0448) |
| IV cereals | | | | | | | | | 0.0399*** | |
| | | | | | | | | | (0.0035) | |
| IV fruits | | | | | | | | | 0.0517*** | -2.8350*** |
| | | | | | | | | | (0.0018) | (0.0611) |
| IV livestock | | | | | | | | | 0.4582*** | -3.1306*** |
| | | | | | | | | | (0.0113) | (0.0737) |
| IV other | | | | | | | | | 0.0610*** | -0.8448*** |
| | | | | | | | | | (0.0134) | (0.0700) |
| IV vegetables | | | | | | | | | -0.0940 | -2.7019*** |
| | | | | | | | | | (0.0882) | (0.1479) |
| **Climate** | | | | | | | | | | |
| Temperature | 131.3135*** | | -3.7055*** | -2.2288*** | -0.3606 | | 1.9898** | -2.3998*** | | |
| | (37.7654) | | (0.8568) | (0.8138) | (0.8774) | | (0.8447) | (0.8344) | | |
| Temperature sq. | -2.3743*** | | 0.0578*** | 0.0243 | -0.0195 | | -0.0827*** | 0.0530*** | | |
| | (0.7077) | | (0.0159) | (0.0154) | (0.0168) | | (0.0166) | (0.0158) | | |
| Rainfall | 5.3279** | | -2.0742*** | -3.2331*** | 0.0483 | | -4.6083*** | 0.2565 | | |
| | (2.2680) | | (0.5954) | (0.5102) | (0.7328) | | (0.5561) | (0.6258) | | |
| Rainfall sq. | -0.0173** | | -0.0593* | 0.0578*** | 0.0107 | | -0.0130 | -0.0089 | | |
| | (0.0075) | | (0.0351) | (0.0092) | (0.0186) | | (0.0103) | (0.0153) | | |
| Temp.*Rainfall | -0.1810** | | 0.0553* | 0.0709*** | -0.1166*** | | 0.1743*** | -0.1009*** | | |
| | (0.0760) | | (0.0302) | (0.0159) | (0.0266) | | (0.0186) | (0.0211) | | |
| Temperature SD | -0.1359 | | -0.0401** | 0.0124 | 0.0509** | | 0.0778*** | 0.0672*** | | |
| | (0.1481) | | (0.0183) | (0.0168) | (0.0211) | | (0.0171) | (0.0179) | | |
| Rainfall seasonality | -0.4966*** | | -0.0978*** | -0.0405*** | -0.0359*** | | -0.0426*** | -0.0723*** | | |
| | (0.1137) | | (0.0082) | (0.0068) | (0.0096) | | (0.0069) | (0.0073) | | |
| **Output prices** | | | | | | | | | | |
| Price cacao | -0.0527 | | | | | | | | | |
| | (0.0331) | | | | | | | | | |
| Price barley | | | 0.0175*** | | | | | | | |
| | | | (0.0035) | | | | | | | |
| Price maize | | | | 0.0060*** | | | | | | |
| | | | | (0.0009) | | | | | | |
| Price oat | | | | | 0.0025 | | | | | |
| | | | | | (0.0016) | | | | | |
| Price sorghum | | | | | | | 0.0022* | | | |
| | | | | | | | (0.0012) | | | |
| Price wheat | | | | | | | | -0.0044** | | |
| | | | | | | | | (0.0018) | | |
| **Inputs** | | | | | | | | | | |
| Wage rate | -0.1098** | | -0.0277*** | -0.0237*** | -0.0282*** | | -0.0208*** | -0.0676*** | | |
| | (0.0439) | | (0.0058) | (0.0032) | (0.0054) | | (0.0035) | (0.0049) | | |
| Plot size | -0.1931 | | -0.1832*** | -0.3054*** | -0.3343*** | | -0.2355*** | -0.1760*** | | |
| | (0.3221) | | (0.0637) | (0.0557) | (0.0680) | | (0.0568) | (0.0595) | | |
| **Socio-demographic characteristics** | | | | | | | | | | |
| Age | 0.0472 | | 0.0063 | -0.0109 | -0.0071 | | -0.0013 | 0.0003 | | |
| | (0.0393) | | (0.0101) | (0.0093) | (0.0096) | | (0.0094) | (0.0098) | | |
| Indigenous | -3.7818*** | | -0.3957 | 0.7759*** | 0.2917 | | -0.0299 | 0.5707* | | |
| | (1.2270) | | (0.3490) | (0.2858) | (0.3052) | | (0.3087) | (0.3095) | | |
| Schooling | -0.0181 | | -0.0155 | -0.0786*** | -0.0514* | | -0.0408 | -0.0261 | | |
| | (0.0992) | | (0.0275) | (0.0244) | (0.0286) | | (0.0249) | (0.0260) | | |
| **Access to markets** | | | | | | | | | | |
| Mobile | -3.1518*** | | -1.1888*** | -1.6841*** | -1.2896*** | | -1.4693*** | -1.0155*** | | |
| | (1.0904) | | (0.2843) | (0.2573) | (0.2752) | | (0.2624) | (0.2785) | | |
| Internet | 5.3967*** | | 0.5005 | 0.1201 | -0.0539 | | -0.6180 | -0.2093 | | |
| | (1.8273) | | (0.4568) | (0.3851) | (0.5001) | | (0.3923) | (0.4012) | | |
| City | -0.2624** | | -0.0471 | -0.0310 | -0.0334 | | -0.0286 | -0.0434 | | |
| | (0.1298) | | (0.0305) | (0.0290) | (0.0294) | | (0.0290) | (0.0293) | | |
| Road density | -1.7090 | | -3.8564*** | -2.7851*** | -4.4436*** | | -2.1062*** | -1.6983** | | |
| | (1.4150) | | (0.7025) | (0.6495) | (0.7098) | | (0.6501) | (0.6790) | | |
| **Soils** | | | | | | | | | | |
| Vertisol | 0.0420** | | 0.0107*** | -0.0045* | 0.0059** | | 0.0091*** | 0.0111*** | | |
| | (0.0170) | | (0.0033) | (0.0026) | (0.0029) | | (0.0027) | (0.0031) | | |
| Feozem | -0.2002* | | 0.0224*** | 0.0102** | 0.0161*** | | 0.0154*** | 0.0291*** | | |
| | (0.1032) | | (0.0049) | (0.0047) | (0.0048) | | (0.0047) | (0.0050) | | |
| Regosol | 0.0438** | | 0.0203*** | 0.0217*** | 0.0166*** | | 0.0221*** | 0.0384*** | | |
| | (0.0203) | | (0.0046) | (0.0040) | (0.0043) | | (0.0042) | (0.0043) | | |
| Cambisol | 0.0134 | | 0.0164*** | 0.0178*** | 0.0135*** | | 0.0294*** | 0.0375*** | | |
| | (0.0147) | | (0.0050) | (0.0046) | (0.0048) | | (0.0047) | (0.0049) | | |
| Constant | -1,759.5472*** | | 71.6950*** | 58.5955*** | 36.8964*** | | 11.8266 | 50.1742*** | | |
| | (494.0435) | | (11.0964) | (10.7588) | (11.4454) | | (10.9388) | (11.0635) | | |
| Observations | 8,622 | | 592,806 | 592,806 | 592,806 | | 592,806 | 592,806 | 1,009,590 | 1,009,590 |

Top: robust standard errors in parentheses (using bootstrap and clusters at the farm level, 1000 reps.)
Bottom: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

# Table 3.23 Nested Logit model 31 alternatives (2-2014)

| | | | | Fruits | | | | | Livestock | |
|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **apples** | **avocado** | **bananas** | **grape** | **lemon** | **mango** | **oranges** | **cattle** | **pigs** | **poultry** |
| | | | | **Climate** | | | | | | |
| Temperature | | -0.4174 | 1.7756 | 8.5637 | 0.4016 | 0.6189 | 2.5061 | 0.3193 | | 0.6821 |
| | | (5.4596) | (5.9300) | (5.2741) | (5.7967) | (5.9525) | (5.9605) | (0.4184) | | (0.7094) |
| Temperature sq. | | 0.0486 | 0.0265 | -0.2016 | 0.0552 | 0.0338 | -0.0011 | -0.0151* | | -0.0215 |
| | | (0.1383) | (0.1450) | (0.1295) | (0.1428) | (0.1454) | (0.1456) | (0.0091) | | (0.0163) |
| Rainfall | | 0.5381 | 0.2942 | 5.5219 | 0.3544 | -3.0967 | -1.5489 | -0.8236*** | | -0.5851* |
| | | (3.7246) | (4.1916) | (6.3837) | (4.1626) | (4.2038) | (4.1853) | (0.3070) | | (0.3467) |
| Rainfall sq. | | -0.0630 | -0.0162 | -1.6394*** | -0.0186 | -0.0152 | -0.0026 | -0.0066 | | -0.0040 |
| | | (0.0513) | (0.0549) | (0.3677) | (0.0548) | (0.0549) | (0.0548) | (0.0053) | | (0.0065) |
| Temp.*Rainfall | | 0.0585 | 0.0474 | 0.0413 | 0.0302 | 0.1718 | 0.0933 | 0.0518*** | | 0.0375** |
| | | (0.1766) | (0.1914) | (0.2731) | (0.1905) | (0.1922) | (0.1914) | (0.0128) | | (0.0151) |
| Temperature SD | | -0.4938*** | -0.5299*** | -0.0762 | -0.4472*** | -0.3898*** | -0.3054** | 0.0458*** | | 0.0392 |
| | | (0.1248) | (0.1264) | (0.0790) | (0.1285) | (0.1257) | (0.1246) | (0.0117) | | (0.0246) |
| Rainfall seasonality | | -0.0101 | -0.0598 | -0.0005 | -0.0650 | 0.0680 | -0.0973** | -0.0150** | | -0.0015 |
| | | (0.0458) | (0.0482) | (0.0422) | (0.0481) | (0.0484) | (0.0479) | (0.0062) | | (0.0103) |
| | | | | **Output prices** | | | | | | |
| Price avocado | | 0.0003 | | | | | | | | |
| | | (0.0023) | | | | | | | | |
| Price bananas | | | 0.0107*** | | | | | | | |
| | | | (0.0015) | | | | | | | |
| Price grape | | | | -0.0238*** | | | | | | |
| | | | | (0.0071) | | | | | | |
| Price lemon | | | | | -0.0009 | | | | | |
| | | | | | (0.0011) | | | | | |
| Price mango | | | | | | -0.0181*** | | | | |
| | | | | | | (0.0026) | | | | |
| Price oranges | | | | | | | -0.0011 | | | |
| | | | | | | | (0.0014) | | | |
| Price cattle | | | | | | | | -0.0167*** | | |
| | | | | | | | | (0.0056) | | |
| Price pigs | | | | | | | | | | 0.0082 |
| | | | | | | | | | | (0.0118) |
| | | | | **Inputs** | | | | | | |
| Wage rate | | 0.0716*** | 0.0806*** | 0.1116*** | 0.0740*** | 0.0742*** | 0.0522** | 0.0043 | | -0.0132 |
| | | (0.0253) | (0.0257) | (0.0246) | (0.0258) | (0.0257) | (0.0258) | (0.0069) | | (0.0084) |
| Plot size | | -0.0252 | -0.0869 | 0.0634 | 0.0365 | -0.2055* | 0.0747 | 0.1929*** | | 0.0132 |
| | | (0.1026) | (0.1110) | (0.0952) | (0.1098) | (0.1103) | (0.1054) | (0.0246) | | (0.0336) |
| | | | | **Socio-demographic characteristics** | | | | | | |
| Age | | -0.0271 | 0.0012 | 0.0158 | -0.0204 | 0.0210 | -0.0041 | 0.0003 | | 0.0047 |
| | | (0.0187) | (0.0184) | (0.0155) | (0.0181) | (0.0187) | (0.0177) | (0.0059) | | (0.0134) |
| Indigenous | | -0.8267 | -3.0629*** | 1.2713 | -2.1665** | -1.0465 | -1.5171 | -0.7258*** | | -0.2262 |
| | | (0.8622) | (1.0489) | (0.9445) | (1.0163) | (1.0260) | (1.0325) | (0.2146) | | (0.3871) |
| Schooling | | -0.0857* | -0.0047 | -0.0589 | -0.0683 | 0.0034 | -0.0142 | 0.0116 | | -0.0034 |
| | | (0.0500) | (0.0478) | (0.0444) | (0.0488) | (0.0483) | (0.0468) | (0.0228) | | (0.0379) |
| | | | | **Access to markets** | | | | | | |
| Mobile | | 0.0902 | 0.6008 | -1.0092* | 0.5309 | 0.2825 | 0.3250 | -0.3299* | | -0.9410*** |
| | | (0.4700) | (0.4861) | (0.5744) | (0.4807) | (0.4854) | (0.4709) | (0.1898) | | (0.3070) |
| Internet | | 1.0018 | 0.5114 | -0.3973 | 0.4367 | 0.2509 | -0.7494 | -2.1411*** | | -0.0131 |
| | | (0.6994) | (0.7197) | (0.6013) | (0.7794) | (0.7317) | (0.6735) | (0.2348) | | (0.4749) |
| City | | -0.0070 | -0.1379*** | -0.0510 | -0.0240 | -0.0083 | -0.0611* | 0.0661*** | | 0.0339 |
| | | (0.0445) | (0.0400) | (0.0313) | (0.0353) | (0.0360) | (0.0331) | (0.0171) | | (0.0274) |
| Road density | | -4.2309* | -3.0989 | 16.7758*** | -2.4347 | -3.7489 | -2.6371 | -0.0035 | | 1.8143** |
| | | (2.5133) | (2.6363) | (3.2840) | (2.6236) | (2.7204) | (2.6445) | (0.4731) | | (0.7954) |
| | | | | **Soils** | | | | | | |
| Vertisol | | -0.0542*** | -0.0325 | -0.0369*** | -0.0340 | -0.0462** | -0.0413* | 0.0053** | | -0.0061 |
| | | (0.0206) | (0.0212) | (0.0131) | (0.0213) | (0.0209) | (0.0211) | (0.0023) | | (0.0039) |
| Feozem | | -0.0143 | 0.0033 | 0.0169*** | 0.0006 | -0.0074 | -0.0065 | 0.0047** | | -0.0048 |
| | | (0.0105) | (0.0115) | (0.0060) | (0.0115) | (0.0116) | (0.0115) | (0.0022) | | (0.0047) |
| Regosol | | 0.0181 | 0.0292* | 0.0453*** | 0.0071 | 0.0138 | 0.0261 | 0.0162*** | | 0.0054 |
| | | (0.0181) | (0.0175) | (0.0105) | (0.0178) | (0.0174) | (0.0174) | (0.0036) | | (0.0051) |
| Cambisol | | -0.0078 | -0.0002 | 0.0000 | 0.0007 | 0.0013 | -0.0153 | 0.0208*** | | 0.0196** |
| | | (0.0105) | (0.0113) | (0.0000) | (0.0111) | (0.0111) | (0.0115) | (0.0045) | | (0.0079) |
| Constant | | 4.0554 | -32.9066 | -85.8729 | -10.8134 | -17.5199 | -27.4727 | 3.1455 | | -9.2929 |
| | | (56.1107) | (63.7309) | (55.6681) | (61.8585) | (64.0289) | (63.8487) | (5.5507) | | (9.1908) |
| | | 60,795 | 60,795 | 60,795 | 60,795 | 60,795 | 60,795 | 62,451 | | 62,451 |

Top: robust standard errors in parentheses (using bootstrap and clusters at the farm level, 1000 reps.)
Bottom: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

# Table 3.24 Nested Logit model 31 alternatives (3-2014)

| | Other | | | | | | | Vegetables | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **VARIABLES** | **alfalfa** | **beans** | **chilli** | **cotton** | **potato** | **soy** | **sugarc** | **gretom** | **melon** | **onion** | **redtom** | **squash** | **waterm** |
| **Climate** | | | | | | | | | | | | | |
| Temperature | 7.5880*** | | 1.9295*** | 5.2561*** | -0.9386 | 24.9327*** | 8.3071*** | -1.553*** | -1.9553*** | 1.5634*** | | -2.1970*** | -0.0203 |
| | (0.4500) | | (0.2919) | (0.8268) | (0.7255) | (3.7563) | (0.4438) | (0.3669) | (0.7395) | (0.5891) | | (0.3924) | (0.7657) |
| Temp. sq. | -0.1697*** | | -0.0428*** | -0.1330*** | 0.0491*** | -0.5938*** | -0.1768*** | 0.0332*** | 0.0276 | -0.0443*** | | 0.0505*** | -0.0028 |
| | (0.0108) | | (0.0075) | (0.0205) | (0.0161) | (0.0857) | (0.0100) | (0.0089) | (0.0201) | (0.0150) | | (0.0096) | (0.0179) |
| Rainfall | 3.6918*** | | 0.0197 | -5.9336*** | 4.2666*** | -10.2773*** | 1.5585*** | 0.6682** | -6.6715*** | -0.0949 | | 0.4906 | -0.1728 |
| | (0.5097) | | (0.2325) | (1.4431) | (0.7503) | (1.7877) | (0.1762) | (0.3181) | (1.1683) | (0.4794) | | (0.3037) | (1.1346) |
| Rainfall sq. | -0.0656*** | | -0.0049* | -0.0137 | -0.0234 | -0.2964*** | -0.0250*** | -0.040*** | -0.0956** | -0.0418** | | -0.0407*** | -0.063*** |
| | (0.0148) | | (0.0028) | (0.0307) | (0.0167) | (0.0378) | (0.0028) | (0.0105) | (0.0387) | (0.0173) | | (0.0107) | (0.0154) |
| Temp.*Rainfall | -0.1689*** | | 0.0056 | 0.2273*** | -0.197*** | 0.6122*** | -0.0312*** | 0.0136 | 0.3211*** | 0.0391** | | 0.0168 | 0.0651 |
| | (0.0206) | | (0.0095) | (0.0689) | (0.0308) | (0.0755) | (0.0084) | (0.0107) | (0.0572) | (0.0191) | | (0.0116) | (0.0447) |
| Temp. SD | 0.1170*** | | 0.0873*** | 0.2277*** | 0.0287 | 0.0542*** | -0.0105 | 0.1306*** | 0.1142*** | 0.1176*** | | 0.1302*** | 0.1657*** |
| | (0.0072) | | (0.0095) | (0.0155) | (0.0234) | (0.0180) | (0.0135) | (0.0243) | (0.0248) | (0.0243) | | (0.0219) | (0.0276) |
| Rainfall S. | -0.0825*** | | -0.0594*** | -0.1180*** | -0.099*** | -0.0776*** | -0.0499*** | 0.0026 | -0.0206 | -0.0433*** | | -0.0079 | -0.0022 |
| | (0.0065) | | (0.0061) | (0.0127) | (0.0105) | (0.0099) | (0.0050) | (0.0099) | (0.0145) | (0.0110) | | (0.0088) | (0.0118) |
| **Output prices** | | | | | | | | | | | | | |
| Price alfalfa | 0.0039*** | | | | | | | | | | | | |
| | (0.0012) | | | | | | | | | | | | |
| Price beans | | | | | | | | | | | | | |
| Price chilli | | | -0.0091*** | | | | | | | | | | |
| | | | (0.0022) | | | | | | | | | | |
| Price cotton | | | | 0.0005 | | | | | | | | | |
| | | | | (0.0075) | | | | | | | | | |
| Price potato | | | | | -0.0045 | | | | | | | | |
| | | | | | (0.0054) | | | | | | | | |
| Price soy | | | | | | -0.0004 | | | | | | | |
| | | | | | | (0.0046) | | | | | | | |
| Price sugarc | | | | | | | 0.0309*** | | | | | | |
| | | | | | | | (0.0033) | | | | | | |
| Price gretom | | | | | | | | -0.0046 | | | | | |
| | | | | | | | | (0.0029) | | | | | |
| Price melon | | | | | | | | | -0.0046 | | | | |
| | | | | | | | | | (0.0069) | | | | |
| Price onion | | | | | | | | | | -0.0069** | | | |
| | | | | | | | | | | (0.0032) | | | |
| Price redtom | | | | | | | | | | | | | |
| Price squash | | | | | | | | | | | | -0.0016 | |
| | | | | | | | | | | | | (0.0028) | |
| Price waterm | | | | | | | | | | | | | -0.0023 |
| | | | | | | | | | | | | | (0.0025) |
| **Inputs** | | | | | | | | | | | | | |
| Wage rate | -0.0107*** | | -0.0198*** | -0.0118 | -0.0238** | 0.0353*** | -0.0041 | 0.0164*** | 0.0288*** | 0.0188*** | | 0.0032 | 0.0069 |
| | (0.0039) | | (0.0057) | (0.0077) | (0.0115) | (0.0054) | (0.0037) | (0.0058) | (0.0072) | (0.0063) | | (0.0081) | (0.0109) |
| Plot size | -0.0144 | | 0.2524*** | 0.1461*** | 0.6340*** | 0.5397*** | 0.2097*** | 0.0230 | -0.0422 | 0.0649 | | -0.0630 | 0.0088 |
| | (0.0288) | | (0.0536) | (0.0506) | (0.1272) | (0.0682) | (0.0383) | (0.0754) | (0.0824) | (0.0698) | | (0.0665) | (0.1000) |
| **Socio-demographic characteristics** | | | | | | | | | | | | | |
| Age | 0.0056 | | -0.0126** | 0.0148 | 0.0081 | -0.0143 | 0.0152** | -0.0038 | -0.0302** | -0.0029 | | -0.0250*** | -0.0248* |
| | (0.0040) | | (0.0050) | (0.0149) | (0.0104) | (0.0096) | (0.0066) | (0.0086) | (0.0151) | (0.0107) | | (0.0086) | (0.0129) |
| Indigenous | 0.1480 | | 0.5533*** | -0.5072 | -2.480*** | -1.1023*** | -0.6994*** | -0.3866 | -4.3779*** | -0.6990* | | -0.0554 | -0.6832 |
| | (0.1761) | | (0.1860) | (0.5484) | (0.8660) | (0.3209) | (0.1516) | (0.2714) | (1.2701) | (0.4009) | | (0.2699) | (0.4557) |
| Schooling | 0.0617*** | | 0.0085 | 0.0115 | 0.0114 | -0.0333 | 0.0166 | 0.0257 | -0.0568 | 0.0038 | | -0.0686** | 0.0088 |
| | (0.0130) | | (0.0204) | (0.0356) | (0.0338) | (0.0321) | (0.0258) | (0.0326) | (0.0510) | (0.0315) | | (0.0309) | (0.0382) |
| **Access to markets** | | | | | | | | | | | | | |
| Mobile | 0.5445*** | | 0.5876*** | 1.3090*** | 0.1730 | 1.0254*** | 0.2230* | -0.805*** | -0.9095** | -0.7672** | | -1.2418*** | 0.3014 |
| | (0.1059) | | (0.1550) | (0.3944) | (0.3537) | (0.2143) | (0.1344) | (0.2821) | (0.4022) | (0.3518) | | (0.2879) | (0.3717) |
| Internet | 0.4643** | | 1.1862*** | -0.3266 | 2.4988*** | 2.1691*** | 1.7093*** | -1.088*** | -2.0456*** | -0.5408 | | -0.3566 | -1.464*** |
| | (0.1947) | | (0.1980) | (0.3516) | (0.3371) | (0.5385) | (0.5145) | (0.3327) | (0.4698) | (0.3393) | | (0.3204) | (0.4866) |
| City | -0.0214*** | | -0.0220*** | -0.0036 | -0.0048 | 0.0599*** | -0.0981*** | -0.0028 | 0.0312** | -0.0277 | | 0.0159 | 0.0079 |
| | (0.0059) | | (0.0073) | (0.0075) | (0.0142) | (0.0149) | (0.0107) | (0.0141) | (0.0155) | (0.0173) | | (0.0151) | (0.0175) |
| Road density | 6.5886*** | | 3.0000*** | 4.9249*** | 2.3397** | 4.5840*** | 3.5605*** | 2.3002*** | 3.6551** | 3.1221*** | | 2.7287*** | 1.5729 |
| | (0.3283) | | (0.4541) | (1.2824) | (1.0639) | (0.8968) | (0.4611) | (0.6997) | (1.4698) | (0.6537) | | (0.5850) | (1.2585) |
| **Soils** | | | | | | | | | | | | | |
| Vertisol | 0.0019 | | -0.0034 | -0.0094* | 0.0178*** | -0.0063* | -0.0112*** | -0.0015 | -0.0315*** | 0.0264*** | | -0.0041 | -0.041*** |
| | (0.0018) | | (0.0029) | (0.0056) | (0.0033) | (0.0036) | (0.0027) | (0.0046) | (0.0111) | (0.0046) | | (0.0048) | (0.0078) |
| Feozem | 0.0052*** | | 0.0009 | 0.0043 | -0.020*** | 0.0053 | -0.0059*** | -0.0050 | -0.0310*** | 0.0095* | | -0.0156*** | -0.0125** |
| | (0.0014) | | (0.0020) | (0.0061) | (0.0060) | (0.0046) | (0.0021) | (0.0037) | (0.0075) | (0.0049) | | (0.0039) | (0.0057) |
| Regosol | 0.0227*** | | 0.0107*** | 0.0118*** | -0.0018 | -0.0302*** | -0.0109*** | 0.0011 | -0.0190*** | 0.0215*** | | -0.0116*** | -0.0095** |
| | (0.0025) | | (0.0026) | (0.0043) | (0.0086) | (0.0063) | (0.0023) | (0.0033) | (0.0042) | (0.0042) | | (0.0040) | (0.0045) |
| Cambisol | 0.0303*** | | -0.0066* | 0.0420*** | 0.0056 | -0.0952*** | -0.0378*** | -0.0076 | -0.0101 | -0.0052 | | -0.0174** | -0.0026 |
| | (0.0036) | | (0.0039) | (0.0143) | (0.0062) | (0.0331) | (0.0032) | (0.0061) | (0.0131) | (0.0104) | | (0.0069) | (0.0088) |
| Constant | -82.391*** | | -20.172*** | -51.583*** | -0.1522 | -269.209*** | -100.590*** | 9.8386*** | 28.5040*** | -16.301*** | | 19.5010*** | -6.9229 |
| | (4.8236) | | (3.0508) | (8.6380) | (8.6842) | (40.4766) | (4.9755) | (3.5051) | (6.9255) | (5.9354) | | (3.8687) | (8.1440) |
| | 224,735 | | 224,735 | 224,735 | 224,735 | 224,735 | 224,735 | 21,276 | 21,276 | 21,276 | | 21,276 | 21,276 |

Top: robust standard errors in parentheses (using bootstrap and clusters at the farm level, 1000 reps.)
Bottom: robust standard errors in parentheses (clustering at the farm level)
*** p<0.01, ** p<0.05, * p<0.1. SD: Standard Deviation.

**Table 3.25 Hausman tests (unrestricted MNL models)**

| Equation | Exclusion (2012) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Beverage | Cattle | Fruits | Other | Pigs | Poultry | Vegetables |
| **Beverage** | - | 705.68*** | 378.79*** | 547.52*** | 54.56*** | 38.22 | 142.48*** |
| **Cattle** | 290.37*** | - | 963.64*** | 1436.66*** | 63.83*** | 44.83** | 221.75*** |
| **Fruits** | 196.83*** | 544.35*** | - | 969.72*** | 58.66*** | 36.42 | 120.19*** |
| **Other** | 264.92*** | 482.07*** | 681.14*** | - | 59.84*** | 58.38*** | 183.65*** |
| **Pigs** | 86.97*** | 138.73*** | 98.19*** | 134.90*** | - | 25.00 | 67.26*** |
| **Poultry** | 72.77*** | 115.00*** | 93.32*** | 152.18*** | 23.71 | - | 51.27*** |
| **Vegetables** | 133.61*** | 146.63*** | 278.67*** | 319.67*** | 51.05*** | 43.26** | - |

| Equation | Exclusion (2014) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Beverage | Cattle | Fruits | Other | Pigs | Poultry | Vegetables |
| **Beverage** | - | 417.56*** | 415.95*** | 406.48*** | 51.95*** | 37.61 | 123.90*** |
| **Cattle** | 253.77*** | - | 895.04*** | 578.40*** | 62.71*** | 47.44** | 169.35*** |
| **Fruits** | 255.55*** | 261.98*** | - | 627.67*** | 54.39*** | 35.09 | 100.01*** |
| **Other** | 174.55*** | 305.70*** | 668.86*** | - | 66.90*** | 44.16** | 110.24*** |
| **Pigs** | 129.90*** | 78.36*** | 137.32*** | 110.39*** | - | 18.54 | 40.69* |
| **Poultry** | 49.76*** | 135.11*** | 111.80*** | 119.49*** | 22.72 | - | 54.87*** |
| **Vegetables** | 95.35*** | 133.18*** | 188.99*** | 136.06*** | 55.93*** | 27.56 | - |

Note: Hausman tests estimated via the suest command in Stata 15.0 (clusters at the farm level)
Null hypothesis: difference in coefficients not systematic
*** p<0.01, ** p<0.05, * p<0.1
Chi2(d.f.): 29

## Table 3.26 Predicted probabilities 2061-2080, NAS-2012 (% of total number of plots allocated to an agricultural commodity)

| | | Average probability | | CCSM4 | | | | | | | | MIROC5 | | | | | | | | MRI-CGCM3 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | | RCP2.6 | | RCP4.5 | | RCP6.0 | | RCP8.5 | |
| **Choice** | **Baseline** | **MNL+** | **NL++** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** | **MNL** | **NL** |
| **Alfalfa** | 3.59 | 3.59 | 2.91 | 0.01 | 2.66 | 0.00 | 2.47 | 0.00 | 2.53 | 0.00 | 2.28 | 0.00 | 2.58 | 0.00 | 2.43 | 0.00 | 2.47 | 0.00 | 2.19 | 0.03 | 2.72 | 0.00 | 2.58 | 0.00 | 2.58 | 0.00 | 2.29 |
| **Apples** | 0.28 | 0.28 | 0.36 | 0.01 | **0.39** | 0.00 | **0.34** | 0.00 | **0.40** | 0.00 | **0.43** | 0.00 | **0.41** | 0.00 | **0.42** | 0.00 | **0.42** | 0.00 | **0.45** | 0.00 | **0.38** | 0.00 | **0.41** | 0.00 | **0.40** | 0.00 | **0.45** |
| **Avocado** | 0.61 | 0.61 | 0.61 | 0.01 | 0.55 | 0.00 | 0.46 | 0.00 | 0.50 | 0.00 | 0.43 | 0.00 | 0.53 | 0.00 | 0.48 | 0.00 | 0.49 | 0.00 | 0.41 | 0.05 | 0.54 | 0.00 | 0.51 | 0.00 | 0.51 | 0.00 | 0.43 |
| **Bananas** | 0.40 | 0.40 | 0.64 | 0.02 | **0.56** | 0.00 | **0.55** | 0.00 | **0.54** | 0.00 | **0.46** | 0.00 | **0.51** | 0.00 | **0.44** | 0.00 | **0.48** | 0.00 | 0.37 | 0.01 | **0.53** | 0.00 | **0.47** | 0.00 | **0.49** | 0.00 | 0.37 |
| **Barley** | 2.23 | 2.23 | 8.77 | **7.03** | **10.02** | **25.07** | **11.22** | **25.65** | **11.20** | **53.69** | **13.05** | **10.31** | **10.42** | **27.17** | **11.28** | **22.34** | **11.23** | **42.35** | **12.85** | **11.95** | **9.90** | **16.01** | **10.45** | **17.22** | **10.58** | **31.90** | **11.92** |
| **Beans** | 6.94 | 6.94 | 3.08 | 3.39 | 3.36 | 0.86 | 3.56 | 0.81 | 3.57 | 0.07 | 3.89 | 3.79 | 3.45 | 2.77 | 3.63 | 2.38 | 3.61 | 1.08 | 3.92 | 2.84 | 3.35 | 3.07 | 3.47 | 2.29 | 3.49 | 1.94 | 3.79 |
| **Cacao** | 0.36 | 0.36 | 0.34 | 0.00 | 0.08 | 0.00 | 0.02 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 |
| **Cattle** | 18.26 | 18.26 | 17.38 | 17.60 | 17.21 | 8.77 | 15.71 | 8.09 | 15.97 | 1.50 | 12.36 | 12.87 | 16.87 | 7.33 | 16.12 | 7.26 | 15.85 | 2.24 | 14.01 | 13.38 | 16.96 | 10.71 | 16.74 | 10.75 | 16.62 | 4.05 | 15.15 |
| **Chillies** | 0.91 | 0.91 | 2.91 | 0.09 | **3.04** | 0.01 | **3.08** | 0.00 | **3.08** | 0.00 | **3.10** | 0.11 | **3.08** | 0.19 | **3.14** | 0.06 | **3.11** | 0.05 | **3.19** | 0.40 | **3.01** | 0.31 | **3.08** | 0.10 | **3.07** | 0.27 | **3.17** |
| **Coffee** | 1.15 | 1.15 | 1.17 | 0.00 | **1.43** | 0.00 | **1.49** | 0.00 | **1.49** | 0.00 | **1.51** | 0.00 | **1.50** | 0.00 | **1.51** | 0.00 | **1.51** | 0.00 | **1.51** | 0.01 | **1.46** | 0.00 | **1.50** | 0.00 | **1.50** | 0.00 | **1.51** |
| **Cotton** | 1.40 | 1.40 | 2.48 | 0.31 | **2.62** | 0.05 | **2.67** | 0.03 | **2.64** | 0.00 | **2.65** | 0.15 | **2.66** | 0.02 | **2.74** | 0.05 | **2.69** | 0.00 | **2.79** | 0.20 | **2.59** | 0.13 | **2.68** | 0.08 | **2.66** | 0.00 | **2.79** |
| **Grape** | 0.15 | 0.15 | 0.20 | 0.00 | 0.07 | 0.00 | 0.04 | 0.00 | 0.04 | 0.00 | 0.02 | 0.00 | 0.05 | 0.00 | 0.05 | 0.00 | 0.04 | 0.00 | 0.01 | 0.12 | **0.16** | 0.00 | 0.08 | 0.00 | 0.07 | 0.00 | 0.02 |
| **Green tom.** | 0.14 | 0.14 | 0.40 | 0.04 | **0.36** | 0.01 | **0.29** | 0.01 | **0.32** | 0.00 | **0.25** | 0.03 | **0.34** | 0.01 | **0.28** | 0.01 | **0.30** | 0.00 | **0.23** | 0.04 | **0.34** | 0.02 | **0.32** | 0.02 | **0.32** | 0.00 | **0.25** |
| **Lemon** | 0.64 | 0.64 | 0.75 | 0.06 | **0.70** | 0.01 | **0.69** | 0.01 | **0.69** | 0.00 | 0.62 | 0.02 | **0.66** | 0.00 | 0.59 | 0.00 | 0.63 | 0.00 | 0.52 | 0.04 | **0.67** | 0.01 | 0.63 | 0.01 | **0.65** | 0.00 | 0.52 |
| **Maize** | 37.04 | 37.04 | 10.89 | **59.01** | 11.60 | **44.11** | 11.89 | **43.52** | 11.86 | 15.30 | 12.38 | **53.94** | 11.87 | 35.72 | 12.28 | **42.45** | 12.10 | 17.80 | 12.98 | **44.55** | 11.40 | **45.56** | 11.88 | **45.47** | 11.81 | 22.80 | 12.76 |
| **Mango** | 1.15 | 1.15 | 0.74 | 0.16 | 0.91 | 0.03 | 1.02 | 0.02 | 0.96 | 0.00 | 1.06 | 0.05 | 1.00 | 0.01 | 1.15 | 0.01 | 1.07 | 0.00 | **1.30** | 0.11 | 0.93 | 0.03 | 1.07 | 0.02 | 1.04 | 0.00 | **1.32** |
| **Melon** | 0.47 | 0.47 | 0.20 | **3.39** | 0.37 | **3.42** | **0.49** | **3.33** | 0.41 | **3.10** | **0.50** | **4.57** | 0.44 | **9.45** | **0.60** | **5.72** | **0.50** | **14.17** | **0.74** | **2.69** | 0.34 | **5.72** | 0.46 | **4.86** | 0.44 | **12.82** | **0.66** |
| **Oat** | 3.58 | 3.58 | 8.86 | 0.17 | **8.19** | 0.02 | **7.51** | 0.01 | **7.77** | 0.00 | **7.13** | 0.07 | **7.99** | 0.01 | **7.59** | 0.01 | **7.68** | 0.00 | **6.98** | 0.44 | **8.30** | 0.07 | **7.95** | 0.05 | **7.95** | 0.00 | **7.26** |
| **Onion** | 0.37 | 0.37 | 0.40 | 0.01 | 0.23 | 0.00 | 0.15 | 0.00 | 0.15 | 0.00 | 0.07 | 0.00 | 0.19 | 0.00 | 0.13 | 0.00 | 0.14 | 0.00 | 0.07 | 0.01 | 0.24 | 0.00 | 0.19 | 0.00 | 0.18 | 0.00 | 0.09 |
| **Oranges** | 0.78 | 0.78 | 0.72 | 0.00 | **0.83** | 0.00 | **0.91** | 0.00 | **0.90** | 0.00 | **0.99** | 0.00 | **0.85** | 0.00 | **0.89** | 0.00 | **0.90** | 0.00 | **0.95** | 0.00 | **0.81** | 0.00 | **0.85** | 0.00 | **0.86** | 0.00 | **0.91** |
| **Pigs** | 0.22 | 0.22 | 0.67 | **0.97** | **1.35** | **1.12** | **2.94** | **1.15** | **2.68** | **1.05** | **6.31** | **1.11** | **1.73** | **1.23** | **2.53** | **1.30** | **2.80** | **1.51** | **4.66** | **0.56** | **1.58** | **0.89** | **1.88** | **0.87** | **2.00** | **1.29** | **3.52** |
| **Potato** | 0.57 | 0.57 | 2.82 | **5.42** | **3.13** | **15.56** | **3.53** | **16.52** | **3.52** | **24.74** | **4.12** | **11.65** | **3.25** | **15.63** | **3.49** | **17.79** | **3.52** | **20.70** | **3.92** | **11.06** | **3.21** | **15.12** | **3.29** | **16.49** | **3.34** | **24.77** | **3.70** |
| **Poultry** | 0.20 | 0.20 | 0.63 | 0.01 | 0.12 | 0.00 | 0.03 | 0.00 | 0.03 | 0.00 | 0.00 | 0.01 | 0.08 | 0.00 | 0.03 | 0.00 | 0.03 | 0.00 | 0.00 | 0.01 | 0.14 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.01 |
| **Red tomato** | 0.75 | 0.75 | 0.52 | 0.17 | 0.48 | 0.03 | 0.44 | 0.02 | 0.46 | 0.00 | 0.39 | 0.10 | 0.45 | 0.02 | 0.40 | 0.03 | 0.42 | 0.00 | 0.33 | 0.12 | 0.50 | 0.06 | 0.45 | 0.05 | 0.45 | 0.00 | 0.37 |
| **Rice** | 0.25 | 0.25 | 7.63 | 0.18 | **7.40** | **0.31** | **7.41** | **0.37** | **7.16** | **0.46** | **6.66** | 0.10 | **7.28** | 0.09 | **6.96** | 0.15 | **7.05** | 0.03 | **6.57** | 0.24 | **7.25** | 0.18 | **7.16** | 0.09 | **7.16** | 0.00 | **6.72** |
| **Sorghum** | 7.08 | 7.08 | 9.61 | 0.03 | **8.90** | 0.00 | **7.82** | 0.00 | **7.89** | 0.00 | 6.52 | 0.01 | **8.66** | 0.00 | **8.01** | 0.00 | **7.98** | 0.00 | 7.05 | 0.02 | **8.49** | 0.00 | **8.44** | 0.00 | **8.29** | 0.00 | **7.53** |
| **Soy** | 0.58 | 0.58 | 2.34 | 0.00 | **1.88** | 0.00 | **1.51** | 0.00 | **1.48** | 0.00 | **1.00** | 0.00 | **1.73** | 0.00 | **1.46** | 0.00 | **1.46** | 0.00 | **1.08** | 0.01 | **1.81** | 0.00 | **1.68** | 0.00 | **1.64** | 0.00 | **1.26** |
| **Squash** | 0.32 | 0.32 | 0.49 | **0.45** | **0.60** | 0.27 | **0.73** | 0.25 | **0.76** | 0.05 | **0.96** | **0.34** | **0.63** | 0.20 | **0.68** | 0.23 | **0.73** | 0.06 | **0.78** | 0.31 | **0.64** | 0.29 | **0.65** | 0.28 | **0.67** | 0.07 | **0.75** |
| **Sugar cane** | 5.54 | 5.54 | 2.99 | 0.00 | 2.83 | 0.00 | 2.71 | 0.00 | 2.71 | 0.00 | 2.48 | 0.00 | 2.77 | 0.00 | 2.64 | 0.00 | 2.67 | 0.00 | 2.44 | 0.01 | 2.84 | 0.00 | 2.75 | 0.00 | 2.75 | 0.00 | 2.53 |
| **Watermelon** | 0.20 | 0.20 | 0.24 | 0.00 | **0.21** | 0.00 | 0.14 | 0.00 | 0.13 | 0.00 | 0.07 | 0.01 | 0.18 | 0.03 | 0.15 | 0.01 | 0.14 | 0.00 | 0.09 | 0.08 | 0.18 | 0.03 | 0.17 | 0.00 | 0.16 | 0.01 | 0.12 |
| **Wheat** | 3.85 | 3.85 | 8.26 | 1.44 | **7.91** | 0.36 | **8.18** | 0.20 | **8.15** | 0.03 | **8.27** | 0.74 | **7.82** | 0.13 | **7.90** | 0.20 | **7.99** | 0.00 | **7.59** | **10.72** | **8.69** | 1.78 | **8.14** | 1.32 | **8.24** | 0.05 | **7.83** |
| **Total** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** | **100** |
| **Temp. (ºC)*** | | **20.48ºC**** | | +1.29 | | +2.12 | | +2.20 | | +3.42 | | +1.66 | | +2.37 | | +2.29 | | +3.41 | | +1.29 | | +1.77 | | +1.31 | | +2.95 | |
| **Rain (%)*** | | **71.07 mm.**** | | -2.09 | | -7.13 | | -6.62 | | -11.40 | | -3.02 | | -5.74 | | -6.02 | | -7.51 | | -9.80 | | -5.41 | | -10.65 | | -8.26 | |

Average probabilities using data from 2012: Baseline is the current plots' distribution

Bold (red) numbers indicate that the corresponding alternative is more (less) likely to be chosen with respect to the baseline under the corresponding scenario.

*Average change in all sampled plots [minimum and maximum change in brackets]

**Current average temperature and rainfall

+ By definition, the sample average predicted probabilities are equal to the observed sample frequencies when the MNL model includes the intercept. This property does not necessarily mean that this model performs better that other discrete choice models (Cameron and Trivedi, 2011. p. 501)

++ The average predicted probabilities in the sample are no longer equal to the observed frequencies. This does not mean that the NL model fit is poor.

# Table 3.27 Predicted probabilities 2061-2080, NAS-2014 (% of total number of plots allocated to an agricultural commodity)

| Choice | Baseline | Average probability MNL+ | NL++ | CCSM4 RCP2.6 MNL | NL | RCP4.5 MNL | NL | RCP6.0 MNL | NL | RCP8.5 MNL | NL | MIROC5 RCP2.6 MNL | NL | RCP4.5 MNL | NL | RCP6.0 MNL | NL | RCP8.5 MNL | NL | MRI-CGCM3 RCP2.6 MNL | NL | RCP4.5 MNL | NL | RCP6.0 MNL | NL | RCP8.5 MNL | NL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Alfalfa | 3.98 | 3.98 | 2.84 | 0.01 | 2.00 | 0.00 | 1.34 | 0.00 | 1.43 | 0.00 | 0.76 | 0.00 | 1.71 | 0.00 | 1.25 | 0.00 | 1.34 | 0.00 | 0.71 | 0.01 | 2.11 | 0.00 | 1.71 | 0.00 | 1.67 | 0.00 | 0.92 |
| Apples | 0.44 | 0.44 | 0.49 | 0.06 | 0.40 | 0.01 | 0.29 | 0.00 | 0.34 | 0.00 | 0.27 | 0.02 | 0.37 | 0.00 | 0.32 | 0.00 | 0.33 | 0.00 | 0.25 | 0.02 | 0.40 | 0.02 | 0.36 | 0.01 | 0.36 | 0.00 | 0.28 |
| Avocado | 0.57 | 0.57 | 0.81 | 0.03 | 0.86 | 0.01 | 0.88 | 0.01 | 0.92 | 0.00 | 0.96 | 0.02 | 0.87 | 0.01 | 0.87 | 0.01 | 0.89 | 0.00 | 0.91 | 0.14 | 0.84 | 0.02 | 0.85 | 0.02 | 0.86 | 0.00 | 0.87 |
| Bananas | 0.58 | 0.58 | 0.83 | 0.75 | 0.85 | 0.60 | 0.89 | 0.56 | 0.87 | 0.20 | 0.87 | 0.60 | 0.85 | 0.26 | 0.85 | 0.31 | 0.85 | 0.10 | 0.84 | 0.45 | 0.84 | 0.35 | 0.84 | 0.33 | 0.85 | 0.12 | 0.84 |
| Barley | 1.62 | 1.62 | 9.18 | 4.31 | 10.30 | 8.90 | 11.28 | 9.17 | 11.31 | 12.13 | 12.75 | 5.21 | 10.70 | 8.75 | 11.46 | 8.35 | 11.38 | 11.64 | 12.71 | 4.95 | 10.21 | 6.24 | 10.70 | 6.76 | 10.81 | 9.58 | 11.90 |
| Beans | 7.18 | 7.18 | 3.52 | 5.31 | 4.73 | 2.25 | 5.29 | 2.20 | 5.30 | 0.31 | 5.61 | 5.31 | 5.04 | 3.01 | 5.51 | 3.50 | 5.36 | 0.67 | 5.92 | 4.01 | 4.65 | 3.90 | 5.10 | 3.61 | 5.10 | 1.18 | 5.79 |
| Cacao | 0.30 | 0.30 | 0.30 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cattle | 11.88 | 11.88 | 10.10 | 9.90 | 9.93 | 3.17 | 9.18 | 2.97 | 9.26 | 0.32 | 7.94 | 5.54 | 9.74 | 2.15 | 9.55 | 2.47 | 9.21 | 0.42 | 8.85 | 6.40 | 9.67 | 4.50 | 9.70 | 4.26 | 9.58 | 0.87 | 9.23 |
| Chillies | 0.62 | 0.62 | 3.13 | 0.21 | 3.68 | 0.04 | 3.63 | 0.03 | 3.66 | 0.00 | 3.21 | 0.14 | 3.70 | 0.10 | 3.67 | 0.06 | 3.60 | 0.01 | 3.34 | 0.21 | 3.58 | 0.16 | 3.71 | 0.12 | 3.68 | 0.05 | 3.56 |
| Coffee | 2.26 | 2.26 | 2.26 | 0.01 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.02 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 | 0.00 | 2.56 |
| Cotton | 1.59 | 1.59 | 2.08 | 0.02 | 2.02 | 0.00 | 1.54 | 0.00 | 1.55 | 0.00 | 0.95 | 0.00 | 1.83 | 0.00 | 1.60 | 0.00 | 1.50 | 0.00 | 1.11 | 0.01 | 1.85 | 0.00 | 1.83 | 0.00 | 1.74 | 0.00 | 1.44 |
| Grape | 0.32 | 0.32 | 0.32 | 0.01 | 0.18 | 0.00 | 0.10 | 0.00 | 0.11 | 0.00 | 0.06 | 0.01 | 0.14 | 0.00 | 0.11 | 0.00 | 0.11 | 0.00 | 0.05 | 0.04 | 0.22 | 0.01 | 0.16 | 0.00 | 0.15 | 0.00 | 0.07 |
| Green tom. | 0.35 | 0.35 | 0.28 | 0.32 | 0.27 | 0.15 | 0.24 | 0.15 | 0.24 | 0.03 | 0.19 | 0.27 | 0.26 | 0.11 | 0.23 | 0.16 | 0.23 | 0.03 | 0.19 | 0.23 | 0.26 | 0.18 | 0.25 | 0.19 | 0.25 | 0.04 | 0.21 |
| Lemon | 0.52 | 0.52 | 0.90 | 2.12 | 1.02 | 6.12 | 1.16 | 6.32 | 1.13 | 5.84 | 1.29 | 3.81 | 1.05 | 2.67 | 1.09 | 4.60 | 1.12 | 1.70 | 1.21 | 1.98 | 1.00 | 1.58 | 1.04 | 2.15 | 1.05 | 0.67 | 1.13 |
| Maize | 36.11 | 36.11 | 12.09 | 48.82 | 12.56 | 31.27 | 12.45 | 31.30 | 12.49 | 8.43 | 12.42 | 41.66 | 12.64 | 22.71 | 12.86 | 28.99 | 12.62 | 9.98 | 13.03 | 36.39 | 12.39 | 34.17 | 12.74 | 34.23 | 12.61 | 14.22 | 13.17 |
| Mango | 0.98 | 0.98 | 0.90 | 0.72 | 0.99 | 0.59 | 1.03 | 0.53 | 0.99 | 0.13 | 1.00 | 0.36 | 1.03 | 0.11 | 1.12 | 0.19 | 1.05 | 0.02 | 1.17 | 0.58 | 1.00 | 0.49 | 1.07 | 0.36 | 1.05 | 0.03 | 1.20 |
| Melon | 0.33 | 0.33 | 0.57 | 4.60 | 0.42 | 7.72 | 0.32 | 8.66 | 0.35 | 19.01 | 0.27 | 7.43 | 0.38 | 24.00 | 0.31 | 11.55 | 0.33 | 34.45 | 0.23 | 4.53 | 0.46 | 10.08 | 0.38 | 9.59 | 0.38 | 25.88 | 0.27 |
| Oat | 3.39 | 3.39 | 9.04 | 0.24 | 7.97 | 0.03 | 7.10 | 0.02 | 7.39 | 0.00 | 6.50 | 0.11 | 7.67 | 0.02 | 7.10 | 0.02 | 7.27 | 0.00 | 6.20 | 0.65 | 8.33 | 0.12 | 7.72 | 0.10 | 7.71 | 0.00 | 6.67 |
| Onion | 0.41 | 0.41 | 0.32 | 0.01 | 0.46 | 0.00 | 0.62 | 0.00 | 0.59 | 0.00 | 0.80 | 0.01 | 0.52 | 0.00 | 0.63 | 0.00 | 0.62 | 0.00 | 0.83 | 0.01 | 0.46 | 0.00 | 0.53 | 0.00 | 0.54 | 0.00 | 0.73 |
| Oranges | 1.75 | 1.75 | 0.91 | 0.00 | 0.87 | 0.00 | 0.81 | 0.00 | 0.81 | 0.00 | 0.71 | 0.00 | 0.84 | 0.00 | 0.80 | 0.00 | 0.80 | 0.00 | 0.73 | 0.00 | 0.87 | 0.00 | 0.84 | 0.00 | 0.84 | 0.00 | 0.78 |
| Pigs | 0.38 | 0.38 | 1.27 | 0.85 | 1.67 | 0.68 | 2.58 | 0.69 | 2.47 | 0.32 | 4.00 | 0.76 | 1.95 | 0.50 | 2.25 | 0.62 | 2.57 | 0.32 | 3.10 | 0.53 | 1.95 | 0.62 | 2.00 | 0.62 | 2.12 | 0.37 | 2.67 |
| Potato | 0.38 | 0.38 | 2.60 | 1.97 | 3.92 | 5.16 | 5.62 | 5.42 | 5.45 | 10.77 | 7.72 | 3.46 | 4.59 | 5.84 | 5.52 | 5.54 | 5.70 | 9.31 | 7.15 | 2.33 | 4.29 | 3.52 | 4.65 | 3.69 | 4.87 | 6.38 | 6.24 |
| Poultry | 0.12 | 0.12 | 0.99 | 0.09 | 0.77 | 0.03 | 0.61 | 0.03 | 0.64 | 0.00 | 0.44 | 0.06 | 0.69 | 0.02 | 0.57 | 0.02 | 0.59 | 0.01 | 0.41 | 0.07 | 0.76 | 0.05 | 0.67 | 0.05 | 0.67 | 0.01 | 0.48 |
| Red tomato | 0.48 | 0.48 | 0.30 | 0.06 | 0.34 | 0.01 | 0.35 | 0.01 | 0.35 | 0.00 | 0.34 | 0.03 | 0.34 | 0.01 | 0.35 | 0.01 | 0.35 | 0.00 | 0.35 | 0.06 | 0.32 | 0.02 | 0.34 | 0.02 | 0.34 | 0.00 | 0.35 |
| Rice | 0.32 | 0.32 | 8.14 | 0.29 | 8.24 | 0.26 | 8.45 | 0.23 | 8.20 | 0.07 | 7.95 | 0.15 | 8.22 | 0.04 | 8.12 | 0.08 | 8.13 | 0.01 | 7.93 | 0.28 | 8.08 | 0.22 | 8.14 | 0.14 | 8.15 | 0.01 | 7.97 |
| Sorghum | 10.14 | 10.14 | 10.48 | 0.07 | 8.98 | 0.00 | 7.37 | 0.00 | 7.47 | 0.00 | 5.57 | 0.02 | 8.37 | 0.00 | 7.36 | 0.00 | 7.35 | 0.00 | 5.87 | 0.04 | 8.54 | 0.00 | 8.19 | 0.00 | 8.01 | 0.00 | 6.60 |
| Soy | 1.06 | 1.06 | 1.77 | 0.00 | 0.39 | 0.00 | 0.08 | 0.00 | 0.08 | 0.00 | 0.01 | 0.00 | 0.22 | 0.00 | 0.08 | 0.00 | 0.08 | 0.00 | 0.01 | 0.00 | 0.35 | 0.00 | 0.18 | 0.00 | 0.16 | 0.00 | 0.04 |
| Squash | 0.36 | 0.36 | 0.29 | 0.70 | 0.24 | 0.55 | 0.19 | 0.55 | 0.20 | 0.20 | 0.14 | 0.58 | 0.22 | 0.40 | 0.19 | 0.47 | 0.19 | 0.20 | 0.14 | 0.43 | 0.23 | 0.49 | 0.22 | 0.49 | 0.21 | 0.22 | 0.16 |
| Sugar cane | 4.27 | 4.27 | 3.15 | 0.01 | 2.34 | 0.00 | 1.58 | 0.00 | 1.62 | 0.00 | 0.81 | 0.00 | 1.98 | 0.00 | 1.45 | 0.00 | 1.49 | 0.00 | 0.83 | 0.01 | 2.25 | 0.00 | 1.90 | 0.00 | 1.86 | 0.00 | 1.09 |
| Watermelon | 0.18 | 0.18 | 0.35 | 0.01 | 0.38 | 0.00 | 0.39 | 0.00 | 0.39 | 0.00 | 0.38 | 0.00 | 0.38 | 0.00 | 0.39 | 0.00 | 0.39 | 0.00 | 0.38 | 0.01 | 0.38 | 0.00 | 0.39 | 0.00 | 0.38 | 0.00 | 0.39 |
| Wheat | 7.13 | 7.13 | 9.79 | 18.50 | 10.68 | 32.44 | 12.07 | 31.16 | 11.86 | 42.24 | 13.53 | 24.43 | 11.12 | 29.31 | 11.82 | 33.04 | 11.96 | 31.13 | 12.98 | 35.62 | 11.17 | 33.23 | 11.24 | 33.25 | 11.44 | 40.35 | 12.41 |
| Total | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Temp. (ºC)* | 20.67ºC** | | | +1.28 | | +2.11 | | +2.19 | | +3.40 | | +1.69 | | +2.41 | | +2.32 | | +3.46 | | +1.31 | | +1.77 | | +1.83 | | +2.96 | |
| Rain (%)* | 66.35 mm.** | | | -1.75 | | -6.63 | | -6.07 | | -10.68 | | -3.67 | | -5.59 | | -6.72 | | -7.92 | | -10.65 | | -5.55 | | -6.28 | | -8.89 | |

Average probabilities using data from 2014: Baseline is the current plots' distribution

Bold (red) numbers indicate that the corresponding alternative is more (less) likely to be chosen with respect to the baseline under the corresponding scenario.

*Average change in all sampled plots [minimum and maximum change in brackets]

**Current average temperature and rainfall

+ By definition, the sample average predicted probabilities are equal to the observed sample frequencies when the MNL model includes the intercept. This property does not necessarily mean that this model performs better that other discrete choice models (Cameron and Trivedi, 2011. p. 501)

++ The average predicted probabilities in the sample are no longer equal to the observed frequencies. This does not mean that the NL model fit is poor.

# Chapter 4 PROCAMPO and farms' technical efficiency: a stochastic frontier analysis

N.B. To improve the quality of this research, I presented previous versions of this chapter at the following conferences.

- August 2018. 2018 Agricultural and Applied Economics Association (AAEA) annual meeting, Washington, D.C. United States: https://ageconsearch.umn.edu/record/274376?ln=en and https://ideas.repec.org/p/ags/aaea18/274376.html
- April 2018. 92$^{th.}$ Annual conference of the Agricultural Economics Society (AES). Warwick, United Kingdom.
- March 2018. Pre-Association of Environmental and Resource Economics World Congress Workshop. Birmingham, United Kingdom.

In some cases, the organisers of such conferences made these versions public as part of the conference proceedings. In some cases, David Maddison and Anindya Banerjee were registered as co-authors of the conference papers. Their contribution to the preparation of the conference papers was minimal. Aside from comments and advice made in the course of supervision there was some editing of the relevant chapter for purposes of reducing its length and rephrasing material for the sake of clarity. I am wholly responsible for the literature review, collection of the data, empirical analysis and interpretation of the results.

## 4.1. Introduction

Renegotiating or withdrawing from the North American Free Trade Agreement (NAFTA) would likely pose significant challenges to the agriculture sector of certain constituent countries. Furthermore, some possible outcomes from ongoing negotiations might well force policy-makers to re-evaluate the effectiveness of public policies on farms' performance thereby helping agriculturalists to adapt to changed circumstances. Since the implementation of NAFTA in 1994, the Government of Mexico has supported a direct cash transfer programme called *'Programa de Apoyos Directos al Campo'* (PROCAMPO) intended to shrink the difference between subsidies paid to domestic and foreign agriculturalists. It replaces the previous price-support policies, which ensured fixed prices to the farmer and has grown to become the Government programme with the largest number of recipients in the rural sector.

PROCAMPO consists of a single payment per hectare of cultivated area given to those farmers that own eligible lands.[131] The government defined the eligible land in 1994 and it is not modifiable. It comprises all agricultural fields where farmers cultivated any of the following crops between the 1992 and 1993 summer-spring agricultural seasons: cotton, rice, safflower, barley, beans, corn, sorghum, soy or wheat.[132] Since 1995, the government has removed restrictions and now agriculturalists can grow any (legal) crop. Eligibility for PROCAMPO payments has therefore become a characteristic of the land, transferable between property owner and tenant, but farmers cannot enrol new fields into the subsidisation programme. Nowadays, the main justification for PROCAMPO is to enhance productivity of Mexican farms (DOF, 1994).

[131] In 2014, small or self-consumption farmers (up to 5 and 0.2 hectares of rain-fed and irrigated lands respectively) receive $1,500 MXN/ha for the first 3 hectares of rain-fed land and $1,300 MXN/ha for the remaining fields. Medium-sized farms (5-20 and 0.2-5 hectares of rain-fed and irrigated lands respectively) receive $963 MXN/ha. Large farms (20 or more and 5 or more hectares of rain-fed and irrigated lands respectively) receive $963 MXN/ha up to 100 hectares of land (DOF, 2013). $1 USD=$13.29 MXN.

[132] Intercropping practices are also eligible but if it includes a perennial crop, the corresponding land was/is not eligible.

Over the period 1994-2015 the average payment per hectare ranged between \$732-\$1,615 MXN/ha (57-126 USD/ha).[133] The PROCAMPO programme covers 10.92 and 3.18 million hectares in the Spring-Summer and Autumn-Winter agricultural seasons respectively (49% and 14% of the total cultivated land in Mexico respectively). It benefits 2.41 million and 0.46 million farmers in both agricultural seasons, respectively. On average, the total budget of PROCAMPO is equivalent to 3.45% of the Gross Domestic Product (GDP) of the arable and livestock farming, forestry use, fishery and hunting sector. Moreover, it currently accounts for 16% of the Secretariat of Agriculture, Livestock and Rural Development, Fisheries and Food's (SAGARPA) budget (see Figure 4.6 in Appendix A4.1).

Previous studies have examined the influence of PROCAMPO on agriculturalists' income, migration and food security. Among others, Sadoulet et al. (2001) find that such transfers create a multiplier income-effect in the *ejidal* sector.[134] The income multiplier ranges between 1.5 and 2.6. Gonzalez-Konig and Wodon (2005) and Scott-Andretta and Cuecuecha (2010) find that PROCAMPO discourages migration from Mexico to the US and increases the use of labour in the production of corn and beans.

Regarding food security, Garcia-Salazar et al. (2011) argue that since corn receives the largest amount of subsidy payments, this programme reduces corn imports by 40.5%. Furthermore, Ruiz-Arranz et al. (2002) find empirical evidence against the conventional wisdom that men just drink away PROCAMPO subsidies and argue that these cash transfers enhance food security through investments in domestic production. Although the existing literature has examined the effects of PROCAMPO on different areas, to the best of our knowledge there is no study investigating the association between the PROCAMPO payments and Technical Efficiency (TE) of the agriculture sector in Mexico.

[133] Measured in constants prices 2013=100
[134] Areas of communal land used for farming activities where members individually exploit designated parcels.

Stochastic Frontier Analysis (SFA) relaxes the implausible assumption that all farms are fully efficient and allows for inefficiencies in the production process. It defines the production frontier as the maximum attainable output that can be produced using existing technology and inputs (Minvel and Latruffe, 2017). Any output-input combination lying behind the frontier indicates the existence of inefficiencies. To measure the extent of Technical Inefficiency (TI), the SFA uses two approaches. The output-oriented (OO) approach explores whether a particular farm can produce a higher level of output using the same amount of inputs. On the other hand, the input-oriented (IO) approach explores whether a farm can produce the same output using fewer inputs. Following previous studies, we use the OO approach, which is the standard method, to examine the effect of PROCAPO on farms' TE.

The primary goal of subsidisation programmes, such as PROCAMPO, is to influence farmers' income, boost productivity, or to prevent beneficiaries from choosing undesired practices. However, subsidy payments might have a positive, neutral or potentially negative influence on farms' TE. For example, whilst some cash transfers might lead the adoption of new knowledge, a process which might increase TE (e.g. Zhu and Oude Lansink, 2010) some recipients might use cash transfers merely to augment their income providing them with less incentives to produce efficiently (e.g. Martin and Page, 1983). Among others, Serra et al. (2008), Kumbhakar and Lien (2010), and Zhu and Oude Lansink (2010) argue that any conclusion concerning the influence of subsidies on farms' TE must be drawn from empirical evidence rather than from theorising.

To investigate the link between PROCAMPO and farms' TE, we use representative cross-sectional data drawn from 33,721 crop farms in Mexico. In so doing, this research contributes to the literature by: (i) providing empirical evidence on the link between agricultural subsidies and TE in a large middle income country where there is no prior evidence concerning any such relationship; (ii) computing observation-specific marginal effects of subsidy payments on farms' TE using Wang's (2002) formula; and, iii) computing percentile-specific marginal effects of subsidy payments on farms' TE using Recentered Influence Function (RIF)-regressions. The computation of such marginal effects allows us to identify differential effects of PROCAMPO on farms' TE. To the best of our knowledge, this is the first study within the subsidies-farms' technical efficiency strand of literature that uses RIF-regressions to show differential/heterogeneous effects of agricultural subsidies on farms' TE. By doing so, one can identify those farmers for whom the subsidy causes remarkable losses of TE and provide policy-makers with new insights.

The remainder of this chapter is structured as follows. Section 4.2 presents an overview of the existing literature investigating the link between agricultural subsidies and farms' TE. Section 4.3 describes the SFA method and the database. Section 4.4 presents the results and discusses a set of policy implications arising out of them. Section 4.5 concludes with some suggestions for further research.

## 4.2. Literature review

For presentation purposes, we organise this section as follows. Subsection 4.2.1 describes the literature survey. It identifies the set of relevant materials for the literature review. Section 4.2.2 briefly describes two methodological approaches that account for technical inefficiencies in farming activities. This subsection discusses the main advantages of the SFA over the Data Envelope Analysis (DEA) method. Subsection 4.2.3 presents an overview of previous studies analysing the association of agricultural subsidies and farms' TE. To guide the implementation of the SFA method, we compare model specifications encountered in the empirical literature, which allows us to place the novelty of this research into the existing literature.

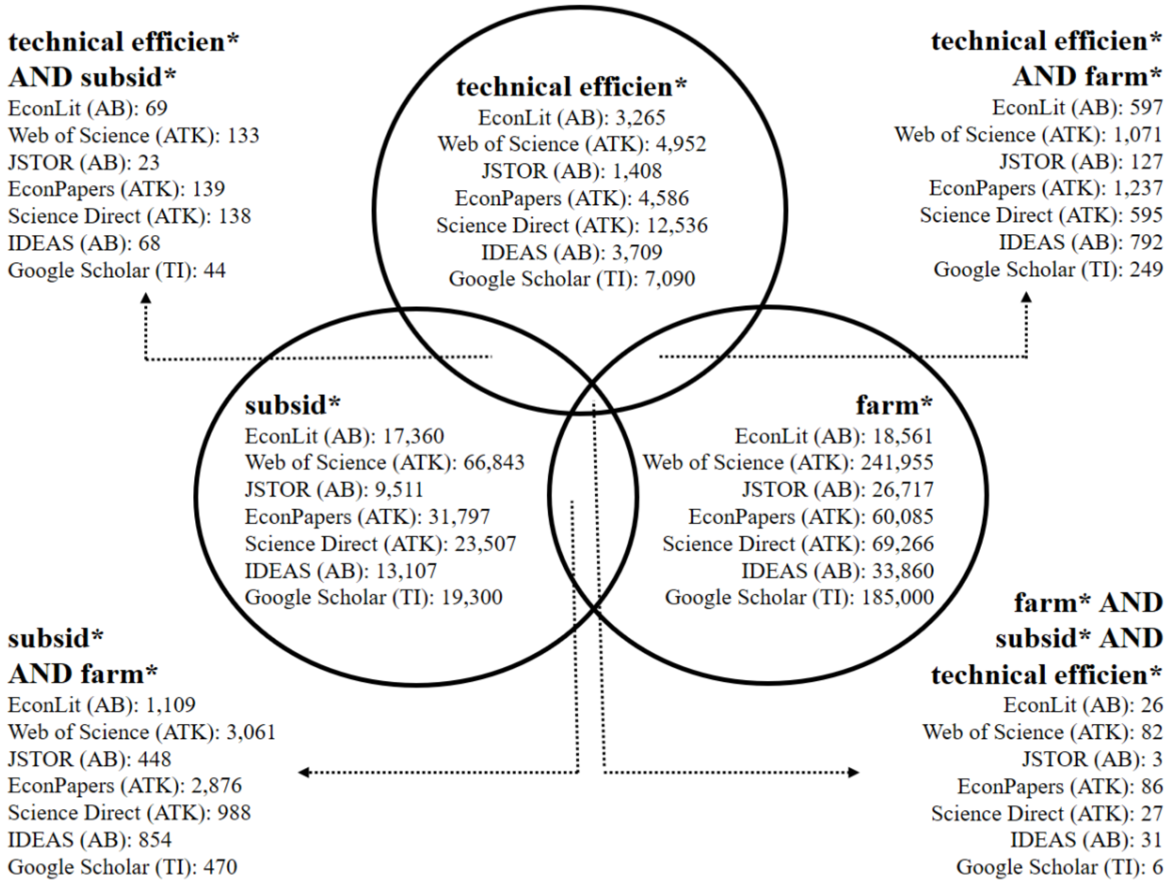
#### *4.2.1. Literature survey*

A systematic literature survey helps us to identify those studies analysing the relationship between subsidy payments and farms' TE. To survey the existing literature, we follow three steps. First, we select a set of search terms closely related to our topic of interest: *subsidies*, *cash transfers*, *farm*, *technical efficiency*, and *agriculture*. Second, we refine our literature search by using different combinations and word endings of these keywords in the EconLit, Web of Science, JSTOR, EconPapers, Science Direct, IDEAS and Google Scholar databases. These materials include published papers, working papers, books, chapters and technical reports. Third, we exclude irrelevant publications by looking at their abstracts and add other relevant materials cited in the initial set of documents. Figure 4.1 shows the literature survey from the abovementioned databases.[135]

The initial set of materials comprises 173 different documents that result from the combination of seven outcomes at the bottom right of figure 4.1.[136] We exclude 95 irrelevant entries because subsidy payments are not part of the analysis and/or simply because the authors do not estimate a second stage regression for technical efficiency.[137]

[135] The search tools limit us to use the same criteria in all of them therefore, we take into account those studies in which the search terms appear either in the abstract (AB), abstract, title or keywords (ATK) or title (TI).
[136] We use those studies where the three search terms, subsidies, farm and technical efficiency, appear in the abstract, title or keywords. We also use agricultur* and cash transfer* as alternative search terms for farm* and subsid* respectively but, the criteria in figure 1 outperform other alternative criteria.
[137] Some authors do not estimate a TI equation either because they assume that farms are fully efficient or because the main purpose of the research is to compute average technical efficiency scores and compare such scores between subsamples, e.g. with and without the subsidy.

**Figure 4.1 Literature survey: agricultural subsidies and technical efficiency**




Source: EconLit, Web of Science, JSTOR, EconPapers, Science Direct, IDEAS and Google Scholar databases.
Note: Number of documents in which the searching criteria appear in the corresponding text; AB: anywhere in the abstract; TI: anywhere in the title; ATK: anywhere in the abstract, title or key words.

To complete the set of materials, we also use two meta-analyses that examine the link between public subsidies and TE in all types of farms (Minviel and Latruffe, 2013, 2014, 2017) and organic farms (Lakner and Breustedt, 2017). As a result, we add 31 materials to the original set of references. Thus, we analyse previous findings encountered in 109 published papers, working papers, technical reports, chapters and books.

### *4.2.2. Methodological approaches*

To identify the association of public subsidies and TE, previous studies apply either the non-parametric DEA or the parametric SFA. Both methods compute strictly positive TE scores, allowing researchers to evaluate the performance of particular farms. The production frontier is the maximum attainable output produced using some inputs and existing technology. Thus, all points behind the frontier are suboptimal. The OO approach computes the size of TI by measuring the distance between the current production level and the production frontier. On the other hand, the IO approach uses the distance between current level of inputs used to produce the corresponding output and the (lower) level of inputs required to produce exactly the same output to measure the size of TIs (Kumbhakar et al. 2015).

Based on the work of Farrell (1957), Charnes et al. (1978) introduce the DEA approach and define it as a mathematical programming model that identifies economic relations such as production functions and efficient production possibilities using real data. Although there are various DEA models in the linear programming literature, Table 4.8 in Appendix A4.2 contains an overview of the Charnes et al. DEA model. The IO (OO) setting minimises (maximises) the difference between (the aggregate of) efficiency scores $\theta$ ($\varphi$) and the adjusted non-Archimedean element ($\varepsilon$) subject to three constraints.

The first constraint states that the sum of input $x_{ij}$ over all farms times the corresponding parameter $\lambda_j$ plus the slack variable $s_i^-$ must be equal to the efficiency score $\theta$ times the observed input value of the corresponding farm. Second, the sum of output $y_{rj}$ over all farms times the corresponding parameter $\lambda_j$ minus the slack variable $s_i^+$ must be equal to the observed output value of the corresponding farm (the observed value of the corresponding farm times the efficiency score ($\varphi$)). Third, all $\lambda_j$ parameters are strictly non-negative. Cooper et al. (2011) state that a farm is fully efficient if and only if $\theta^* = 1$ ($\varphi^* = 1$) and all slack variables $s_i^{-*} = s_r^{+*} = 0$. The farm is weakly efficient if and only if $\theta^* = 1$ ($\varphi^* = 1$) and $s_i^{-*} \neq 0$ and/or $s_r^{+*} \neq 0$ for some input or output. After computing the farm-specific efficiency scores, this approach examines the determinants of inefficiency in a second stage, which is a separate regression, e.g. truncated regressions or censured Tobit models.

Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) introduced the parametric SFA approach into the economic literature. Among others, Kumbhakar and Lovell (2003), Coelli et al. (2005) and Greene (2008) define the SFA as a composite econometric method that accommodates technical inefficiencies and random shocks in the production of commodities (see Table 4.9 in Appendix A4.2 for an overview). These models fit a production frontier using either the Cobb-Douglas (CD), the generalised, the transcendental or the translog (TL) specifications. Using the parameter estimates of the frontier, the SFA then computes observation-specific TE scores.

The SFA approach splits the error term from the production function into a random term ($v$), which accounts for unobserved heterogeneity across farms and unanticipated events (white noise), and a non-negative error term ($u$), which accounts for TI. Therefore, a farm is fully efficient if and only if $u = 0$. The SFA approach further hypothesises the non-negative error term to be a function of variables linked to inefficiency. Thus, this method estimates a separate equation in order to identify the main determinants of TI (Kumbhakar et al, 2015). Recently, empirical studies have used a single-step maximum likelihood (ML) estimator to simultaneously obtaining parameter estimates for both the frontier and the inefficiency equation since this estimator outperforms the two-step procedure (Wang and Schmidt, 2002).

Latruffe et al. (2008) and Justyna (2015) analyse the effect of agricultural subsidies on farms' TE applying both the DEA and SFA approaches. The former study reaches similar conclusions from both methods: the ratio of operational subsidies to total revenue negatively influences TE. Conversely, the latter investigation reaches opposing results; the SFA suggests that total subsidies positively affect TE but the DEA identifies harmful effects on TE of subsidy payments. Although these articles both suffer from data limitations, their findings show that the selection of method matters. Pechrova (2013) argues that changes in input levels in an inefficient farm do not alter TE scores of other farms in the DEA. However, it may modify TE scores in the SFA since this change may affect the random error term. If that happens, estimates from the DEA and SFA may differ and lead to different conclusions. Furthermore, the inclusion of new observations in the sample may shift the frontier in the DEA. In the SFA, TE scores will always be different to those scores calculated before the inclusion of new observations since increasing the sample size has an inevitable effect on the random and non-negative error terms.

To summarize, the main advantages of DEA over SFA are: (i) this method does not impose any assumption on the functional form of the frontier and (ii) it is able to accommodate multiple inputs and outputs in the analysis (Bojnec and Latruffe, 2009 and Minviel and Latruffe, 2017). Regarding the SFA approach its advantages are: (i) deviations from the frontier are not only attributable to TI since it accommodates random shocks and (ii) the single-step ML method is more consistent and efficient than the two-step DEA procedure (Wang and Schmidt, 2002; Latruffe et al. 2008; Bojnec and Latruffe, 2009).

The SFA has, it seems, become the workhorse in the literature investigating the effect of subsidies on TE. According to Minviel and Latruffe (2017), 76% of studies use the SFA approach while 20% use the non-parametric DEA model.[138] Some authors argue that DEA estimates are too sensitive to outliers. Unless we remove outliers from the sample, TE scores resulting from a DEA estimation might be biased.[139] Furthermore, DEA's TE scores are downward-biased because the exclusion of random shocks (Latruffe et al. 2008; Bojnec and Latruffe, 2009; and Mamardashvili and Schmid, 2013). In what follows, the literature review confines itself to those SFA studies that account for random shocks in the frontier and include a subsidy variable in the TI equation.[140]

[138] The remaining set of materials relies on correlation analyses or on comparisons between average technical efficiency scores from different subsamples (subsidised versus not subsidised farmers) calculated with either DEA, SFA, or both.
[139] Boyd et al. (2016) develop the so-called stochastic data envelopment analysis to identify and remove outliers from the sample. Regarding the parametric stochastic frontier analysis, Wheat et al. (2018) propose the contaminated normal-half normal stochastic frontier model to handle outlying observations treating outliers as heteroscedasticity.
[140] Refer to Minviel and Latruffe (2017) for a literature review that includes both DEA and SFA empirical studies.

### *4.2.3. An overview of empirical studies*

#### *4.2.3.1. The frontier and ATE scores*

To guide the specification of our empirical model, Table 4.10 in Appendix A4.3 summarises the set of variables used to fit the frontier function in the existing literature. The dependent variable in the frontier function is either the value of output in currency units, the quantity of output in tonnes/litres, or total sales in currency units of the corresponding agricultural commodities. The former indicator is preferred over quantities because farmers tend to diversify their production efforts and it facilitates the aggregation of distinct products. The value of output in currency units is also preferred over total sales because farmers might store some portion of the produce.

Most studies include land, capital, labour, and intermediate inputs as determinants of the frontier function. To account for land in the production function, previous studies use the total number of hectares, or units of land, utilised to produce the corresponding output. Some studies also include aridity indices and soil characteristics to differentiate the quality of land (Dinar et al., 2007). Accounting for capital is rather less straightforward. Ideally, one should account for the cost of using or non-using biological (natural) capital (air, genetics, pollution sinks, etc.), economic or financial capital (cash, credit/debt, savings, etc.), and manufactured capital (infrastructure, equipment, machinery, facilities, etc.) to produce the corresponding output. Thus, the appropriate value of the cost of capital comprises all the aforementioned types of capital. Most empirical studies using the SFA approach use the self-reported value of or the annual depreciation of manufactured capital. Studies analysing arable activities through the SFA model use either the total value of or annual depreciation of manufactured capital. Regarding non-arable farming, we notice that existing literature uses the total (self-reported) value of milking or breeding cows. Alternatively, capital is accounted for using the size of herd.

Overall, we observe that the existing literature using the SFA approach struggles with the lack of data to measure the cost of capital accurately.

Previous studies use the wage bill, number of workers, or working hours per annum to account for labour in the frontier. Although the former measure captures different levels of workers' skills, it does not consider unpaid family labour. The second measure may misrepresent labour since farmers hire labour sporadically. Working hours have the advantage to include and aggregate all sources of labour, including family labour, into a single variable but this measure does not distinguish between different qualities of labour. To overcome this issue, some studies introduce education indices to differentiate the quality of labour, e.g. high skilled versus low skilled workers (Dinar et al., 2007). Regarding intermediate inputs, the existing literature uses total expenses on purchased inputs, quantities of different inputs, or disaggregated expenses on fertilisers, seeds, crop protection, feed, veterinary fees, energy, and other intermediate inputs.[141]

Some studies introduce other variables as determinants of total output such as access to agricultural extension services that may boost the productivity of inputs, altitude and indicators of policy reforms, e.g. Common Agriculture Policy (CAP) reform (Hadley, 2006; Latruffe et al., 2011). Rather than including subsidy payments in the TI model, Mc Cloud and Kumbhakar (2008) use subsidies as factors of production since Mc Cloud and Kumbhakar argue that these payments facilitate the use of inputs and, consequently, farmers obtain higher levels of output. In panel data studies, a time trend is also an argument of the frontier accounting for technological progress.

[141] Outputs that are used in another stage of the production process should be valued and considered as intermediate inputs in the corresponding agricultural cycle.

**Figure 4.2 Average Technical Efficiency in the existing literature (SFA studies)**


Source: literature review. Note: From the 55 studies analysing the effect of subsidies on farms' TE, 43 papers report the ATE for the corresponding samples or subsamples. Since some of the articles compute ATE scores for different sectors and countries, this graph shows the results from 88 different estimations. In panel data studies, we use the ATE of the panel of farms rather than annual ATE scores.

Using the set of parameter estimates of the frontier, previous studies compute average technical efficiency (ATE) scores. Figure 4.2 displays the distribution of ATE scores in the SFA studies that examine the association of agricultural subsidies and farms' TE. Most of the estimations analyse TE in the production of crops (39%), milk (25%) and crops and livestock (14%). Other studies estimate a SFA model for individual commodities such as beef cattle (e.g. Manevska et al., 2013), pigs (e.g. Rasmussen, 2010), rice and corn (Tian and Wan, 2000), wheat (e.g. Tleubayev et al., 2017), olives (e.g. Zhu et al., 2011), cotton, fruits, and greenhouse horticulture (Karagiannis and Sarris, 2002).

This strand of literature encounters a range of ATE scores between 45% and 96% in regional and country-level studies.[142] The existence of such inefficiencies in the abovementioned farms confirms the appropriateness of the SFA rather than the standard production function, which assumes that farmers are fully efficient. Comparisons between ATE scores from different countries or regions might not be appropriate because these scores come from different frontier functions and samples.

#### *4.2.3.2. Technical inefficiency*

Empirical studies use farmers' characteristics, managerial practices, farms' physical features and external factors to explain TIs. The *age of the farmer* is widely used as an indicator of experience in farming activities therefore older farmers tend to be more efficient (Coelli and Battese, 1996). The literature suggests that more *years of schooling* enhances farmers' abilities to use available resources and existing technologies more efficiently. Such an effect propels farmers closer to the production frontier (Sotnikov, 1998; Dinar et al., 2007). Regarding the set of managerial practices, the share of *family labour* to total labour has a positive effect on TE if family members are better skilled than hired labour or are sufficiently involved in farming

[142] TE scores vary within individual studies. The ATE scores represent the mean of observation-specific TE scores.

activities (Zhu and Lansink, 2010). Conversely, Karagiannis and Sarris (2005) argue that a large share of *hired labour* to total labour incentivises farmers to be more efficient. This happens because farmers look for higher revenues in order to clear higher labour costs. Moreover, farmers can discipline hired workers, which is not always possible with family labour.

The studies in this literature review encounter both a positive and a negative association between *owned land* and TE. The share of owned land to total land negatively influences TE scores since agriculturalists do not pay land rents and, consequently, do not have to look for higher revenues in order to clear such costs (Rezitis et al., 2003). On the other hand, if the farmer owns his/her fields, he/she has more incentive to invest in modern technologies and in soil improvements that reduce the waste of resources in the long run (Zhu and Lansink, 2010). *Total debt* may influence TE in both directions. It may force farmers to produce closer to the frontier in order to face such liabilities or may induce farmers to make inefficient decisions due to the financial stress (Foster and Rauser, 1991).

According to the existing literature, the degree of *diversification* may augment or reduce farms' technical efficiency. Farmers tend to diversify their production efforts because they own plots of land in different locations with different soil qualities (Niroula and Thapa, 2005; Tan et al., 2006). Moreover, farmers diversify in order to cope with production risks such as plagues, water shortages or natural disasters (Latruffe et al., 2011). Another advantage of diversifying production efforts is that certain combinations of crops or alternating crops from one season to another improve soil fertility. On the other hand, agriculturalists should concentrate their efforts in the production of a particular commodity and gain enough experience to produce it more efficiently.

To identify the effect of diversification (specialisation) on technical efficiency, previous studies use any of the following variables: the share of the main output to total output, the Herfindahl index[143] or another composite index. The literature review shows that both hypotheses hold in empirical studies. For example, Manjunatha et al., (2013) and Manevska-Tasevska et al., (2013)[144] encounter a positive relationship between specialisation and technical inefficiency. Among others, Dinar et al., (2007), Bojnec and Latruffe (2009) and Karagiannis and Sarris (2005) identify a negative association between specialisation and technical inefficiency. Other authors, such as Karagiannis and Sarris (2002) and Zhu and Lansink (2010)[145] encounter mixed results.[146]

Among others, Rezitis et al. (2003) argue that allocation of *time to off-farm activities* at the expense of farming may lead to lower levels of TE. In contrast, Bojnec and Ferto (2011) encounter a positive effect of off-farm activities on TE. These authors attribute such effects to the availability of additional funds (off-farm income) to invest in technologies that are more efficient. *Market-oriented* farms tend to be more efficient than other farms since the interaction with other competitors enables them to acquire knowledge and relevant information. However, subsistence agriculturalists might be more efficient than market-oriented farms because of their ability to manage scarce resources (Bojnec and Latruffe, 2009).

Regarding the characteristics of farms, *irrigation* enters in the TI equation as a risk-reducing factor. Despite the intensity of irrigation (or the cost of irrigation) enters in the frontier equation as an input, the existing literature uses the proportion of irrigated land to total land per farm to account for unreliable rainfall. Such ratio has a negative effect on TI (Karagiannis and Sarris, 2002). To control for external factors, previous studies introduce regional dummy variables, indices or dummy variables for soil types, dummy variables for Less Favoured Areas (LFAs), road density, distance to the next farm and dummy variables accounting for structural (policy)

143 Refer to the methodological section for further details.
144 Share of revenue from the main commodity to total revenue.
145 Share of crop revenues to total revenue.
146 Manjunatha et al., (2013), Dinar et al., (2007), Bojnec and Latruffe (2009) and Karagiannis and Sarris (2005) and Karagiannis and Sarris (2002) use the Herfindahl index.

changes and environmental restrictions in the TI model (see Table 4.11 in Appendix A4.3 for the full set of inefficiency explanatory variables). As stated in the introduction, *subsidy payments* might have a positive, neutral or negative influence on farms' TI. In this regard, the next subsection describes such a relationship with more details.

#### *4.2.3.3. Subsidies and technical inefficiency*

Table 4.1 shows the distribution of 243 empirical findings in 55 studies examining the relationship between subsidisation and farms' TE.[147] The lack of information about units of measurement of the subsidy variable prevents us comparing the size of such effects. Instead, we examine the direction of the effect. For purposes of exposition, Table 4.1 displays the effect of subsidisation on TE using six different criteria to group together previous empirical findings: the type of subsidy, the subsidy variable, the analysed sector, the type of data, the studied area, and whether the study addresses endogeneity issues or not. Overall, most of the estimations encounter a significant and negative subsidy-efficiency association (48%). Regarding the type of subsidy, Minviel and Latruffe (2017) identify subsidies that aim to increase investment or production. Production subsidies include input subsidies, output subsidies also known as coupled subsidies,[148] decoupled subsidies,[149] environmental subsidies and subsidies provided to farms in LFAs. See Table 4.1 for the distribution of types and their corresponding effects on TE.[150]

To control for the intensity of the subsidisation of a single farm, SFA models in Table 4.1 use the total value of subsidies, the share of subsidies to total revenue, the share of a particular subsidy to total subsidies, payments per unit of land or head, a dummy variable or the share of subsidised land to total land. Although the existing literature has not reached a consensus about

[147] Some studies present the SFA results for the entire sector, for different subsamples such as farm types, particular areas or countries, ranges of elevation, or quantile regressions.
[148] Subsidies linked to the level of output.
[149] Lump-sum payments.
[150] For a further discussion about the transition from coupled to decoupled subsidies in Europe (Common Agricultural Policy) refer to Anania et. al. (2015).

the standard measure of subsidisation in the SFA model, Minviel and Latruffe (2017) argue that the total value of subsidies per farm may distort parameter estimates due to size effects. Table 4.1 shows that 55.14% of the estimation results use the total value of subsidies in the SFA model. To avoid size effects, Minviel and Latruffe suggest that one should use subsidy rates rather than total subsidy payments. In some cases, data availability does not allow researchers to use a continuous variable in the TI equation, instead, they use a dichotomous variable to indicate whether the farmer receives the subsidy or not.

Grouping together the set of parameter estimates by sector, we observe a clear pattern regarding the effect of subsidisation on different sectors. Most of the studies analyse the production of crops (42%) and milk (29%), where subsidy payments clearly reduce TE. When researchers include both arable and non-arable farming activities in the same analysis (14% of all estimations), we observe a negative effect of subsidies on TE. Recently, organic farms have become popular due to changes in consumers' preferences and the promotion of environmentally friendly food production (Sauer et al., 2002). Since this type of farms must adhere to more stringent environmental regulations, they tend to be less efficient than other farms (Kumbhakar et al., 2009) and according to Table 4.1, subsidy payments exacerbate inefficiencies in organic farms.

The majority of estimations in the literature review use panel or pooled databases from European countries. The main target of such studies is to evaluate the performance of farms under the CAP. Using single farm payments, single area payments, agri-environmental subsidies or payments to LFAs in Europe, these empirical analyses find a negative or a non-significant association in 43% and 30% of total estimations, respectively. Apart from Europe, this literature survey identifies SFA estimations in Canada (Giannakas et al., 2001; Samarajeewa et al., 2012), United States of America (USA) (Serra et al., 2008; Zaeske, 2012), India (Dung et al., 2011) and China (Tian and Wan, 2000; Zhao et al., 2015; Ito, 2015). By simply looking at figures in Table 4.1, the relationship between subsidies and TE in zones other than Europe seems to remain ambiguous. Moreover, other regions than Europe are not widely covered by this literature, especially developing countries in America, Africa and Asia (Minviel and Latruffe, 2017).

**Table 4.1 Relationship between subsidies and technical efficiency in previous studies**

| | Share (%) of the total estimation results | | |
|---|---|---|---|
| | Negative (significant) | Null (non-significant) | Positive (significant) |
| ***All estimations (243 results)*** | **47.74** | 34.98 | 17.28 |
| ***Type of subsidy*** | | | |
| Total subsidies (coupled and decoupled) | **35.12** | 23.14 | 10.74 |
| Input subsidies | 0.83 | 0.41 | **1.24** |
| Agri-environmental subsidies | **7.44** | 4.13 | 3.72 |
| LFA subsidies | 0.41 | **6.20** | 0.41 |
| Investment subsidies | **3.72** | 0.41 | 1.24 |
| Price subsidies | 0.00 | **0.83** | 0.00 |
| ***Subsidy variable*** | | | |
| Value of subsidies (local currency) | 20.16 | **24.69** | 10.29 |
| Subsidies rate (subsidies to revenue) | **17.70** | 2.88 | 1.23 |
| Subsidies rate (subsidies to total subsidies) | **2.47** | 1.23 | 0.41 |
| Subsidies rate (subsidies per land units) | **3.70** | 2.47 | 1.23 |
| Subsidies rate (subsidies per animal) | 0.00 | 0.41 | **1.23** |
| Subsidies dummy (1=the farm receives a subsidy) | **2.88** | 2.47 | 1.23 |
| Proportion of land (subsidised land to total land) | 0.82 | 0.82 | **1.65** |
| ***Sector*** | | | |
| Crops and livestock | **9.47** | 3.70 | 1.23 |
| Crops only | **20.58** | 16.46 | 4.53 |
| Livestock only | 4.12 | **5.76** | 1.23 |
| Organic | **2.47** | 0.82 | 0.82 |
| Dairy | **11.11** | 8.23 | 9.47 |
| ***Data*** | | | |
| Cross-section | 1.65 | 1.23 | **2.06** |
| Panel or pooled data | **46.09** | 33.74 | 15.23 |
| ***Place**** | | | |
| Europe | **43.21** | 30.45 | 13.17 |
| America | 2.06 | **2.88** | 1.23 |
| Asia | 2.47 | 1.65 | **2.88** |
| ***Endogeneity*** | | | |
| Addressing endogeneity issues | 8.23 | **13.58** | 2.47 |
| All explanatory variables are exogenous | **39.51** | 21.40 | 14.81 |

**America*: Alberta (Canada), Kansas (USA), Saskatchewan (Canada), State of Wisconsin (USA), and United States. *Europe*: Austria, Belgium, Crete (Greece), Liberecky (Czech Republic), Czech Republic, Denmark, England, Wales, Finland, France, Schleswig-Holstein (Germany), Germany, Greece, Hungary, Ireland, Italy, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, The Netherlands, and United Kingdom. *Asia*: Bihar and Eastern Uttar Pradesh (India), Wuqi, Dingbian, and Huachi (China), China, Akmola region (Kazakhstan) and Russia.

The SFA model suffers from endogeneity issues if there exists a correlation between inputs and the random error term in the frontier, a correlation between inefficiency effects and the random error term or a correlation between the use of inputs and technical inefficiencies.[151] Latruffe et al. (2017) address the first source of endogeneity by using a 4-step estimation procedure.[152] This issue arises if agriculturalists adjust intermediate inputs (e.g. fertilisers, irrigation or pesticides) as a response to stochastic events (e.g. weather shocks or plagues), which are usually part of the error term. Quiroga et al. (2017) argue that coupled subsidies are endogenous since these payments depend on the level of output and farmers can influence this type of subsidisation. Quiroga et al. (2017) overcome this issue by using a two-stage estimation.[153] Although Latruffe et al and Quiroga et al address the abovementioned sources of endogeneity using four-step and two-step sequential estimations, such results are always less efficient than the single-step estimation results. Unfortunately, the complexity of the model prevented Latruffe et al to fit a single-step model.

## 4.3. Methods and materials

### *4.3.1. Theory*

The economic literature defines the production function as the process of transforming inputs into output(s) and its mathematical representation is as follows:

$$F(\boldsymbol{x}, \boldsymbol{y}) = 0 \tag{4.1}$$

[151] This happens if less efficient farms use large quantities of inputs, which suggests a positive correlation. To the best of our knowledge, this source of endogeneity has not been addressed in the existing literature yet.

[152] First, it regresses the endogenous input on the exogenous variable vector using Ordinary Least Squares (OLS). Second, it computes the non-linear least squares estimator to obtain the full set of parameters in the SF and use the estimated coefficients in the technical inefficiency equation to compute the instrument. Third, it computes the non-linear two-stage least squares to obtain the full set of parameters in the SF using the estimated instrument (step 2) and use the new estimates of the technical inefficiency equation to compute a better instrument compared with the one in step 2. Fourth, it replicates the previous step and uses the estimated instrument in step 3.

[153] First, the ratio of coupled subsidies to total crop production is regressed on a vector of farm characteristics and indicators of policy reforms using the Fixed Effects (FE) or the Random Effects (RE) estimators. Second, a SFA model is estimated in which predicted values of coupled subsidies enter as an additional input in the production function. Actual coupled subsidies and particular decoupled payments are part of the technical inefficiency equation.

Where $\boldsymbol{x}$ and $\boldsymbol{y}$ are $J$ and M dimensional non-negative vectors of inputs and outputs respectively. For a single output, and for simplicity, we can rewrite expression (4.1) as:

$$y = f(\boldsymbol{x}) = f(x_1, \ldots, x_J) \tag{4.2}$$

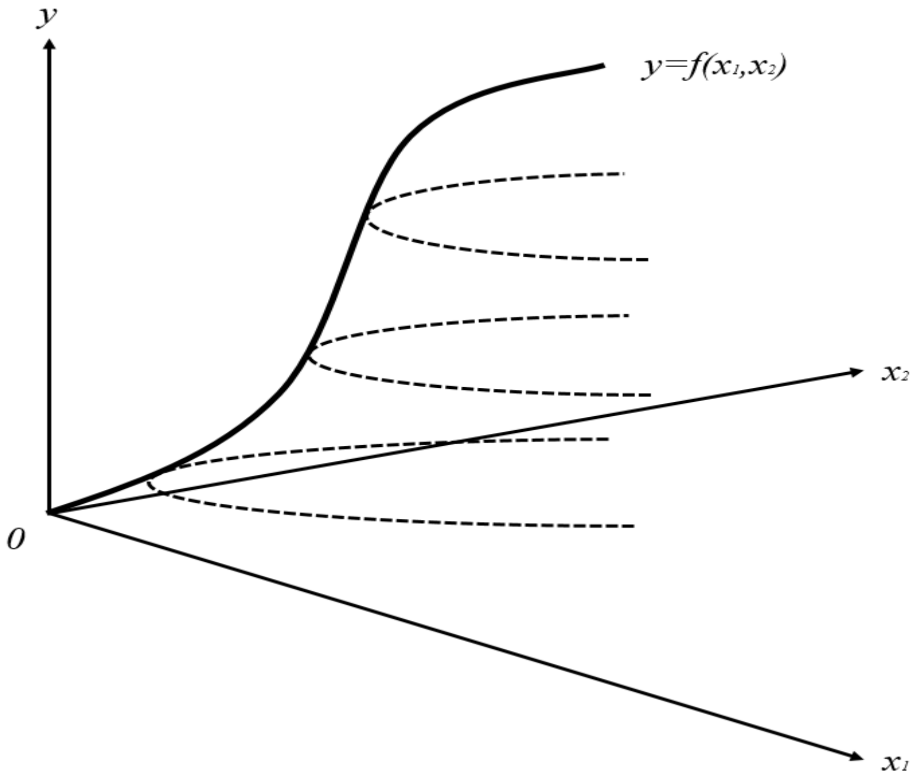
Where $f(.)$ is the maximum attainable output for a given set of inputs. Chambers (1988, p. 9) states that a well-defined function should satisfy certain regularity conditions. First, the production function is finite, non-negative, real-valued and single-valued for all non-negative and finite inputs. Second, the absence of inputs leads to no output. Third, additional inputs will never produce less output (monotonicity). Fourth, the production function is continuous and twice differentiable at any point. Fifth, the input set is convex and therefore, the production function is quasi-concave.

Figure 4.3a displays the feasible production set using two inputs, $x_1$ and $x_2$. The surface denoted by $y = f(x_1, x_2)$ is the maximum achievable output and it bounds the feasible production set. Fixing any of the two inputs to a certain level (e.g. $\overline{x_2}$), we obtain the total product curve for the remaining input, which captures the relationship between the corresponding input and the total output (e.g. $y = f(x_1)$). Thus, holding other inputs constant, the slope of the total product curve $\partial y/\partial x_1$, is the marginal product of $x_1$. To be consistent with theoretical underpinnings, $\partial y/\partial x_1 \geq 0$ and $\partial^2 y/\partial x_1^2 < 0$.[154] Both conditions together guarantee that increasing any input has a non-negative effect on total output.

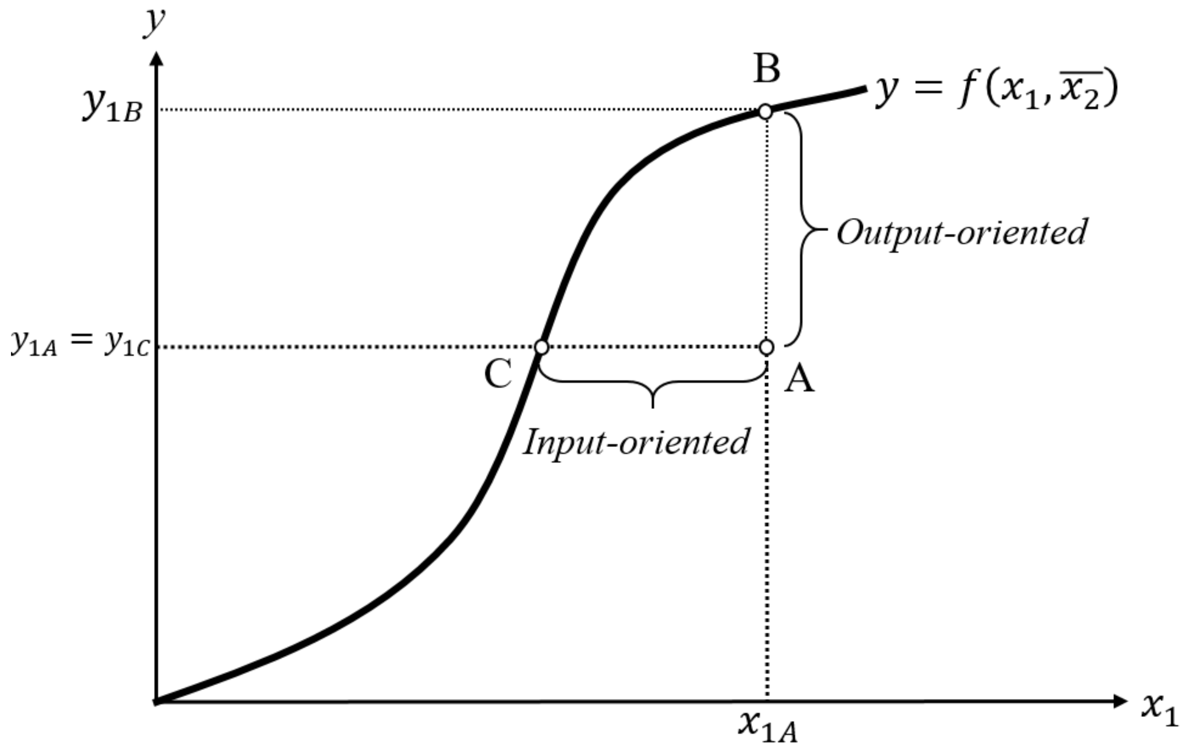
Standard production theory assumes that farms operate along the frontier. Thus, only random noise prevents farms remaining on the production frontier. Nevertheless, the production efficiency literature relaxes this restriction. It allows farmers to operate on or below the frontier due to technical inefficiencies. Figure 3b displays the total product of $x_1$ and illustrates two different measures of technical inefficiency: IO and OO approaches.

[154] Law of diminishing returns.

**Figure 4.3 Single output production function**




**4.3a. Single output production function (two inputs)**




**4.3b. Total product curve ($x_1$)**

Source: adapted from Kumbhakar et al. (2015)

At point A, the OO approach indicates that a higher level of output $y_{1B}$ is achievable using the same level of input $x_{1A}$. Therefore, A is an inefficient production level and the size of technical inefficiency is equal to $(y_{1B} - y_{1A})/y_{1B}$, and consequently, technical efficiency is equal to $y_{1A}/y_{1B}$. Accounting for such inefficiencies, we can rewrite the production function in (4.2) as follows:

$$y = f(\boldsymbol{x}) * \exp(-u) \tag{4.3}$$

Where $u$ is non-negative and measures TI. For small values of $u$, $\exp(-u) \cong 1 - u$. Thus, $\text{TE} = \exp(-u) = 1 - u = 1 - TI$.

Using equation (4.3), we can also measure the effect of increasing inputs on the level of output, or Returns To Scale (RTS). According to the widely known economic literature, a production function is homogeneous if the following condition holds (Kumbhakar et al. 2015):

$$\lambda^{\gamma} y = f\left(\lambda x_1, \dots, \lambda x_J\right) \tag{4.4}$$

Here, condition (4.4) implies that if all inputs rise by the same proportion, $\lambda$, total output increases by $\lambda^{\gamma}$. Then, this production function is homogeneous of degree $\gamma$. For $\gamma > 1$, $\gamma < 1$, or $\gamma = 1$, we observe increasing, decreasing or constant RTS respectively. For homogeneous functions, RTS is the sum of input elasticities:

$$RTS = \sum_{j=1}^{J} \varepsilon_j(\boldsymbol{x}), \text{ where } \varepsilon_j(\boldsymbol{x}) = \frac{\partial \ln f(\cdot)}{\partial \ln x_j}. \tag{4.5}$$

Accounting for TI in the SFA does not alter formulation (4.5) since this term appears additively after taking logs of equation (4.3).

### *4.3.2. Method*

The estimation of the SFA model includes parameter estimates of the frontier and the technical inefficiency functions. To obtain such parameters, we apply the single-step maximum likelihood method.[155] The SFA literature typically uses the CD and/or the TL production functions to identify the frontier in equation 3. The CD function with TIs and in its logarithm form is as follows:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j x_{ij} + v_i - u_i \tag{4.6}$$

Where, $v_i$ is the random noise in the frontier, $u_i$ is the TI term, and $\beta_0 = \ln a$. For strict concavity (quasi-concavity), it requires $0 < \beta_j < 1 \; \forall \, j = 1, \dots, J$, $0 < \sum_{j=1}^{J} \beta_j < 1$ and $a > 0$ ($\beta_j > 0 \; \forall \, j = 1, \dots, J$ and $a > 0$). The CD function is homogeneous of degree $\sum_{j=1}^{J} \beta_j$ and the corresponding elasticities of total output with respect to individual inputs are equal to $\varepsilon_j = \frac{\partial \ln y}{\partial \ln x_j} = \beta_j$. Therefore, $RTS = \sum_{j=1}^{J} \varepsilon_j = \sum_{j=1}^{J} \beta_j$. On the other hand, the TL production function is as follows:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j x_{ij} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} \, x_j x_k + v_i - u_i \tag{4.7}$$

Where $\beta_{jk} = \beta_{kj}$. Unlike the CD function, this specification is not necessarily homogeneous, unless $\sum_{k=1}^{K} \beta_{jk} = 0 \;\; \forall \, j$, and does not assume a constant elasticity of substitution (equals unity in the case of the CD function). The change of total output given by a change in any of the inputs depends on the use of other inputs since $\varepsilon_j = \frac{\partial \ln y}{\partial \ln x_j} = \beta_j + \frac{1}{2} \sum_{k=1}^{K} \beta_{jk} \, x_k$. Hence, RTS are equal to $\sum_{j=1}^{J} \varepsilon_j = \sum_{j=1}^{J} \left( \beta_j + \frac{1}{2} \sum_{k=1}^{K} \beta_{jk} \, x_k \right)$.

Notice that the CD function is a special case of the TL specification. The latter reduces to the former if $\beta_{jk} = 0 \;\; \forall \, jk$. To empirically test for the appropriateness of the two functional forms, the existing literature uses a likelihood ratio test of the form: $LR = -2(L_{CD} - L_{TL})$, where the CD model is nested in the TL model. Here, $L_{CD}$ and $L_{TL}$ are the log-likelihood values of the CD and TL models respectively. The LR-statistic follows a $\chi^2$ distribution with $df_{TL} - df_{CD}$

[155] Refer to Wang and Schmidt (2002) for a further discussion about the superiority of the single-step estimator over the traditional two-step estimation procedure.

degrees of freedom, that is, the difference between the degrees of freedom of the corresponding models (Greene, 2012, p. 526-527).

To identify the two elements of the composite error term in the SFA model, Aigner et al. (1977) and Meeusen and van den Broeck (1977) impose parametric distributions on both terms. The SFA assumes that $v_i$ is an i.i.d. random term with zero mean and constant variance $\left(N(0,\sigma_v^2)\right)$. It accounts for unobserved heterogeneity across farms, stochastic events involved in production activities and errors in the functional form of the frontier. Moreover, it assumes independency between $v_i$ and $u_i$.[156] Regarding the non-negative error term, empirical studies adopt either a half-normal ( $u_i \sim i.i.d.N^+(0,\sigma_u^2)$ ), a truncated-normal ( $u_i \sim i.i.d.N^+(\mu,\sigma_u^2)$ ), or an exponential ($f(u_i) = \frac{1}{\eta} * \exp\left(-\frac{u_i}{\eta}\right)$) distribution for the TI term.

The one-parameter half-normal and exponential distributions cluster the majority of observations close to full-efficiency, that is, the mode of the distribution of TI is zero. This seems to be a restrictive assumption as one may observe high inefficiencies in farming activities. The truncated-normal distribution relaxes such restriction by allowing the mode of $u_i$ to be nonzero. Furthermore, if the mode of the truncated-normal is equal to zero, then the truncated-normal is identical to the half-normal distribution. For these reason, we assume a (more flexible) truncated-normal distribution of TI in the SFA model.

To empirically disentangle the composite error and compute the estimator of $u_i$, the SFA model uses the Jondrow (JLMS) formula (Jondrow et al. 1982, p. 235) along with the previous assumptions:

$$\hat{E}[u|\delta] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(\frac{\delta\lambda}{\sigma}\right)}{1-\Phi\left(\frac{\delta\lambda}{\sigma}\right)} - \left(\frac{\delta\lambda}{\sigma}\right)\right] \tag{4.8}$$

[156] As pointed out in Kumbhakar et al. (2015, p. 55), since $v_i$ captures exogenous shocks, it is unlikely that it might be related to production inefficiencies. However, this random term may capture risks in the production process and farmers' risk-attitudes may be captured by the inefficiency term. See Bandyopadhyay and Das (2006) for further details about such dependency.

Where, $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$, $\phi$ and $\Phi$ stand for the standard normal and cumulative density functions, respectively, and $\delta = v - u$. In the JLMS formula, $e_i = y_i - \widehat{\boldsymbol{\beta}}'\boldsymbol{x_i}$ is the estimator of $\delta_i$. This estimator allows us to obtain observation-specific TE and TI scores.

Among others, Kumbhakar et al. (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994), and Battese and Coelli (1995) argue that the assumption of a truncated-normal distribution ($\mu \neq 0$) enables us to parameterise the expected value of the non-negative error term. Thus, $\mu$ is a linear function of a vector of exogenous variables, $\boldsymbol{z}$, that explains technical inefficiencies:

$$\mu_i = f(\boldsymbol{z_i}) = \gamma_0 + \textstyle\sum_{m=1}^{M} \gamma_m z_{mi} \tag{4.9}$$

Where, $\gamma_m$ are the corresponding parameters. Since both moments of $u_i$ are observation-specific, we can account for heteroscedasticity in the TI term and parameterise $\sigma_u^2$ as in Caudill and Ford (1993), Caudill, Ford, and Gropper (1995) and Hadri (1999).

Following Caudill and Ford, Caudill, Ford, and Gropper and Hadri, Wang (2002) proposes a model in which both $\mu_i$ and $\sigma_u^2$ are linear functions of the same vector of exogenous variables $\boldsymbol{z}$. Wang adds the production uncertainty ($\sigma_i^2$) equation to the traditional model in Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1995),[157] which is as follows:

$$\sigma_i^2 = f(\boldsymbol{z_i}) = \exp(\vartheta_0 + \textstyle\sum_{m=1}^{M} \vartheta_m z_{mi}) \tag{4.10}$$

This model relaxes the assumption that TI increases (decreases) monotonically with the corresponding inefficiency effect. In such a case, the relationship between a variable in the inefficiency equation and technical inefficiency may alternate signs within the sample. For example, the age of the farmer is highly related to his experience therefore, a young farmer gains experience on farming activities as he matures, which at the same time increases his

[157] Equations (4.6) or (4.7) and the parameterisation of $\mu_i$ in equation (4.9)

efficiency; however, an old farmer is likely to face a reduction of his mental and physical capabilities, which negatively influences technical efficiency.[158] This extension of the SFA model adds more complexity to the analysis because the single-step method estimates the parameters of the frontier, technical efficiency ($\mu_i$) and production uncertainty ($\sigma_u^2$) equations simultaneously.

Using Wang's (2002) model, the marginal effect of the $m$-th inefficiency effect on $\mu_i$ is as follows:[159]

$$\frac{\partial \mu_i}{\partial z_m} = \gamma_m \left[1 - \Lambda_i \left[\frac{\phi(\Lambda_i)}{\Phi(\Lambda_i)}\right] - \left[\frac{\phi(\Lambda_i)}{\Phi(\Lambda_i)}\right]^2\right] + \vartheta_m \frac{\sigma_i}{2}\left[(1 + \Lambda_i^2)\left[\frac{\phi(\Lambda_i)}{\Phi(\Lambda_i)}\right] + \Lambda_i \left[\frac{\phi(\Lambda_i)}{\Phi(\Lambda_i)}\right]^2\right] \quad (4.11)$$

Where $\Lambda_i = \mu_i / \sigma_{u,i}$ and $\vartheta_m$ is the $m$-th corresponding coefficient in the production uncertainty equation. These marginal effects are observation-specific and their signs reveal the direction of the association of elements in $\boldsymbol{z}$ and TI.

Linking observation-specific TE scores and marginal effects allows us to see if there are differential effects of PROCAMPO on TE within the sample. Furthermore, we use RIF-regressions to examine differential effects of PROCAMPO on farms' TE. This method is similar to a standard Ordinary Least Squares (OLS) regression but the dependent variable ($u = -\ln(TE)$) is replaced by its RIF function. For a quantile analysis, Firpo et al. (2009) defines the RIF function as follows:

$$RIF(u; q_\tau) = q_\tau + \frac{\tau - \mathbb{1}(\mathbf{u} \leq q_\tau)}{f_u(q_\tau)} \quad (4.12)$$

Where $q_\tau$ is the $\tau$-th quantile of the unconditional distribution of $u$ (maximum value of $u$ in the corresponding quantile), $\tau$ is the quantile, $f_u(q_\tau)$ is the probability density function of $u$

[158] Wang (2002) finds that including square terms to capture non-linear effects (of age) on technical inefficiency lead to non-compelling results.
[159] If $\sigma_u^2$ is not parameterised, the second term in the right-hand side of Wang's (2002) formula vanishes in equation (4.11).

evaluated at $q_\tau$, and $\mathbb{1}(\mathbf{u} \leq q_\tau)$ is an indicator variable equals one if the outcome value $(u)$ is less than or equal to $q_\tau$ and equal to zero otherwise.[160]

### *4.3.3. Data description*

To estimate the SFA model, we use information from the NAS-2014. The National Institute of Statistics and Geography (INEGI by its acronym in Spanish) releases the National Agricultural Survey (NAS). It contains data on 66,483 farms and is a representative sample of the 34 major agriculture commodities. The lack of information on perennial crops and livestock, e.g. value of milking cows, age of perennial trees/plants, or age of breeding pigs/cows, prevents us to compute the cost of capital for these farms. Moreover, the production cycle of some perennial crops and livestock activities typically last more than one year, e.g. the production of avocado or fattening cattle, and then some farms may not report the corresponding annual value of output in the NAS.[161] Additionally, PROCAMPO does not cover the production of perennial crops and livestock activities. Therefore, the dependent variable in the production frontier is the value of output(s) from arable activities that last at most one agricultural year, that is, we drop farms that do not derive 100% of their output from annual crops (farms that report some output from perennial crops or livestock activities are not part of the main analysis). To aggregate all agricultural commodities produced within the corresponding farm into a single category, we use self-reported farm gate prices.[162] Since we use the value of the produce and not the marketed output, the dependent variable does not suffer from the storage effect.

[160] For a further discussion about the advantages of unconditional over conditional quantile regressions approaches refer to Borah and Basu (2013). Overall, the conditional quantile regression (alternative method) identifies the effect of an explanatory variable on a specific quantile of the outcome (dependent) variable. To do that, the conditional quantile regression assess such an effect using specific values of the remaining covariates. Borah and Basu (2013) argue and provide empirical evidence that the results from the conditional quantile regression are not always interpretable in a policy or population context. These quantile effects are usually valid for the corresponding quantile and not for the whole sample or population. Conversely, unconditional quantile regressions such as the RIF-function provide generalizable results since this method computes quantile-specific marginal effects using the (entire) distributions of other covariates in the model.

[161] For instance, a farmer cultivating avocados may report zero output in 2014 because avocado trees are not in the productive phase.

[162] If the farmer does not report farm gate prices, we use averages of farm gate prices at municipality-level instead.

In line with the literature review in section 4.2, the SFA model includes measures of capital, land, labour, and intermediate inputs purchased from outside the farm in the OO frontier equation. The total ownership cost of capital per farm controls for different capital endowments. The NAS contains detailed information on all types of machinery and equipment, which allows us to compute the corresponding ownership costs. According to Edwards (2015), the total ownership cost ($TOC_{il}$) is equal to:

$$TOC_i = \sum_{l=1}^{L}(CR_{il} + TIH_{il}) \tag{4.13}$$

$$CR_{il} = (D_{il} * CRF_{li}) + (SV_{il} * r)$$

$$D_{il} = PP_{il} - SV_{il}$$

$$SV_{il} = PP_{il} * RVF_{il}$$

$$TIH_{il} = 0.01 * (PP_{il} + SV_{il})/2$$

where $CR_{il}$ is the capital recovery cost of the $l$-th machinery or equipment, $TIH_{il}$ are taxes, insurances and housing costs, $D_{il}$ is total depreciation, $CRF_{li}$ stands for the capital recovery factor in Edwards (2011), $SV_{il}$ represents the salvage value, $r$ is the real interest rate,[163] $PP_{il}$ is the current list price,[164] and $RVF_{il}$ is the remaining value factor in Edwards (2011).[165] Using available data, we compute the total ownership cost of tractors, ploughs, cutters/slicers, harvesters, planters, balers, fumigators, disc arrows, and threshing machines. Some farms substitute tractors with a yoke of oxen. In this regard, the NAS only collects data on whether the farmer uses oxen or not. Since 20% of farms in the sample use this type of capital, we account for this using a dummy variable in the frontier equation. Unfortunately, data on buildings and facilities is not available in the NAS. Total land utilised to produce the composite

[163] We use an interest rate of 3.25%, which is the 1995-2014 average in Mexico.

[164] We use prices of machinery and equipment released by SAGARPA. The list is available on: http://www.sagarpa.gob.mx/agricultura/Precios/Paginas/PreciosdeMaquinariaAgricola.aspx

[165] The capital recovery factors and salvage values are available on https://www.extension.iastate.edu/agdm/crops/html/a3-29.html. For purchase prices of equipment and machinery refer to http://www.sagarpa.gob.mx/agricultura/Precios/Paginas/PreciosdeMaquinariaAgricola.aspx

output is also included in the SFA equation. To control for labour, we use the total number of working hours spent on farming activities per farm in the 2014 agricultural year. It includes working hours from full-time workers, temporary workers, '*jornaleros',*[166] and family members. Regarding intermediate inputs, we aggregate together all annual expenses into a single indicator (see Appendix A4.4 for further details).

To explain technical inefficiencies in farming activities, we use the standard set of explanatory variables in the literature. Characteristics of the farmer include their age and years of schooling. Regarding managerial practices, we use the share of owned land to total land, the share of hired labour to total labour, the Herfindahl (diversification) index,[167] the share of irrigated area to total area, and a dummy variable for farms selling agricultural commodities abroad directly, especially in the USA market. According to section 4.2.3.2, total debt and off-farm income may determine the size of TIs. However, the NAS does not collect information on off-farm activities, remittances, or total debt. We acknowledge that not all forms of financial capital are accounted for in the model since there is a delay between incurring expenditures and receiving revenue from harvest even in the production of annual crops. To investigate the association of PROCAMPO and farms' TI, we use a dummy variable. The NAS comprises self-reported data on whether the corresponding farm receives PROCAMPO or not.

After removing entries with missing data, impossible values and farms with perennial crops or livestock activities, the database contains 33,721 valid observations. We exclude 5,070 farms that do not report socio-demographic characteristics of the farmer, age, and years of schooling. Also excluded from the database are the 5,371 farms that do not report or report impossible information on output(s), working hours, intermediate inputs, or proportions of irrigated areas (e.g. none working hours in the agricultural year, zero expenses on intermediate inputs or

[166] Employees hired for sporadic activities (per day) such harvesting activities.

[167] The Herfindahl index is equal to $HI_i = \sum_{j=1}^{J} \left(A_{ji}/TA_i\right)^2$, where $A_{ji}$ is the total area allocated to crop $j$ and $TA_i$ total land in farm $i$.

proportions of irrigated land to total land greater than 100%). We also remove 22,321 farms from the sample, which allocate their production efforts to perennial crops or livestock activities. Thus, the final sample comprises data on 33,721 farms that derive 100% of their revenue from annual (or seasonal) crops. Table 4.2 displays definitions, summary statistics and expected signs of the corresponding variable in the frontier and technical inefficiency models.

Table 4.2 shows that 46% of farms in the sample received the subsidy payment in the 2014 agricultural year. In average, we observe that beneficiaries of PROCAMPO obtain higher revenues but also, utilise larger amounts of capital, land and intermediate inputs that non-recipients. Conversely, non-beneficiaries tend to use labour more intensively than farmers receiving PROCAMPO.

Agriculturalists are on average 57 years old and have 6 years of academic studies, which is equivalent to a primary school education. Overall, most of the farmers are the owners of the sampled fields (82% of the total farmland). The production of agricultural commodities mainly relies on family labour (76% of total working hours). There exists a farmers' specialisation towards particular crops such as corn, beans, sorghum and wheat (Herfindahl index equals 0.91).

**Table 4.2 Definitions, descriptive statistics and expected signs**

| Variable | Description | Units | Mean | | SD | | Min. | | Max. | | Sign |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Stochastic Frontier equation*** | | | | | | | | | | | |
| | | | P | WP | P | WP | P | WP | P | WP | |
| *Output* | Value of the produce (all agricultural commodities) | $*1,000 | 449.47 | 372.28 | 1,335.31 | 1,435.63 | 0.15 | 0.15 | 23,900.00 | 23,800.00 | NA |
| *Capital* | Total ownership cost of capital | $*1,000 | 92.16 | 40.35 | 212.19 | 144.02 | 0.00 | 0.00 | 3,867.87 | 2,799.85 | + |
| *Land* | Total utilised agricultural land to produce | has | 36.43 | 23.92 | 117.47 | 126.68 | 0.02 | 0.01 | 6,055.41 | 8,221.00 | + |
| *Labour* | Total labour including full-time, temporary, 'jornaleros' and family workers | hrs*1,000 | 5.54 | 6.34 | 12.74 | 23.26 | 0.05 | 0.05 | 575.33 | 1,288.28 | + |
| *Inputs* | Annual expenses on intermediate inputs | $*1,000 | 283.36 | 201.32 | 1,616.29 | 3,239.09 | 0.00 | 0.00 | 174,000.00 | 427,000.00 | + |
| *Oxen* | Farms using a yoke of oxen | 0,1 | 0.19 | 0.21 | - | - | 0.00 | 0.00 | 1.00 | 1.00 | |
| ***Technical inefficiency equation*** | | | | | | | | | | | |
| *Age* | Age of the farmer | years | 58.81 | 55.24 | 13.74 | 14.47 | 16.00 | 16.00 | 100.00 | 100.00 | $\pm$ |
| *Schooling* | Farmer's education | years | 6.01 | 6.22 | 4.83 | 4.84 | 0.00 | 0.00 | 24.00 | 26.00 | - |
| *Owned* | Ratio of owned land to total agricultural land | % | 83.48 | 80.98 | 32.87 | 37.19 | 0.00 | 0.00 | 100.00 | 100.00 | - |
| *Hired* | Ratio of hired labour to total labour | % | 24.58 | 23.41 | 32.29 | 32.98 | 0.00 | 0.00 | 100.00 | 100.00 | - |
| *Herfindahl* | Herfindahl index (the closer to one, the closer to full specialisation) | 0-1 | 0.89 | 0.93 | 0.19 | 0.16 | 0.17 | 0.21 | 1.00 | 1.00 | $\pm$ |
| *Irrigated* | Ratio of irrigated land to total agricultural land | % | 32.23 | 27.99 | 43.67 | 42.50 | 0.00 | 0.00 | 100.00 | 100.00 | - |
| *Abroad* | Farm directly selling some of the produce abroad (1=yes and 0=no) | 0,1 | 0.004 | 0.004 | 0.06 | 0.06 | 0.00 | 0.00 | 1.00 | 1.00 | - |
| *Procampo* | Farm receives PROCAMPO (1=yes and 0=no) | 0,1 | 0.46 | | - | | 0.00 | | 1.00 | | $\pm$ |

P: the farmer receives PROCAMPO (15,420 farms), NP: the farmer does not receive PROCAMPO (18,301 farms)
Source: National Agricultural Survey (2014) and SAGARPA (2014)

Almost one third of the sampled fields have an irrigation system (30% of total farmland). In addition, few farms sell their produce abroad directly. Although Mexico exports large quantities of agricultural commodities, farmers usually sell their output(s) to intermediaries (42% of the total number of arable-farms in Mexico), food processors (9%), and other buyers, who finally sell these products abroad, especially in the US market.[168] Therefore, this explains why only 0.4% of farms in the sample sell some of the produce abroad directly (see Table 4.2). The following section examines the effect such variables on farms' TE.

## 4.4. Results

To present the set of findings, we organise this section as follows. First, we analyse the parameter estimates of the frontier model, the ATE scores and the corresponding input elasticities. Second, we discuss the implications of parameter estimates of the TI equation. We perform a set of RIF-regressions to compute marginal effects of the subsidy variable on TE for each percentile of the distribution and show the distribution of the observation-specific marginal effects of PROCAMPO on farms' TE scores. Third, we develop a set of robustness checks to verify the consistency of our findings.

### *4.4.1. Production frontier*

The SFA model uses equations (4.6), (4.7), (4.9) and (4.10) to examine the PROCAMPO-TE link. Table 4.3 shows the parameter estimates of the OO production frontier. To identify the functional form that better fits our data, we estimate both the CD and the TL models with and without technical inefficiencies. To minimise biases resulting from omitted variables, we use regional fixed effects to control for heterogeneous climate, economic policies, traditions and other regional factors in the frontier models.[169] SFA models (1) and (4) in Table 4.3 assume

[168] http://www.inegi.org.mx/est/contenidos/proyectos/encuestas/agropecuarias/ena/ena2014/doc/tabulados.html
[169] We create eight dummy variables. North West: Baja California, Baja California Sur, Chihuahua, Durango, Sinaloa and Sonora. North East: Coahuila, Nuevo Leon and Tamaulipas. West: Colima, Jalisco, Michocan and Nayarit. East: Hidalgo, Puebla, Tlaxcala and Veracruz. Centre North: Aguascalientes, Guanajuato, Queretaro, San Luis Potosi and Zacatecas. Centre South: CDMX, Estado de Mexico and Morelos. South West: Chiapas, Guerrero and Oaxaca. South East: Campeche, Quintana

that there are no technical inefficiencies in production activities, that is, all parameters in the mean and variance TI equations are equal zero. So that, all deviations from the frontier arise from random shocks. SFA models (2) and (5) parameterise the mean TI equation but assume that all parameters in the variance TI equation are zero. Allowing for non-monotonic effects, SFA models (3) and (6) parameterise both moments of the TI error term as in Wang (2002).

Before analysing the set of findings, we test for the existence of technical inefficiencies in the agriculture sector (hypothesis 1) and for the appropriateness of the Wang's model (hypothesis 2). Hypothesis 1 states that farms are fully efficient, and consequently, parameters in the (mean and variance) TI equation are simultaneously zero. Regarding hypothesis 2, it states that the parameterisation of the variance of TI is not appropriate, then, all coefficients are zero. Table 4.12 in Appendix A4.4 indicates that all slopes in the (mean) TI equations are different from zero, that is, we can reject hypothesis 1. This result holds for both the TL and CD functions. Moreover, Table 4.12 shows evidence in favour of the appropriateness of Wang's model rather than the standard approach. The likelihood ratio test indicates that we can reject hypothesis 2. This test indicates that the parameterisation of production uncertainty matters. Therefore, SFA models (3) and (6) should be preferred over models (1-2) and (4-5) respectively.

We also test for the best functional form between models (3) and (6), that is, all square and interaction terms are equal to zero in the TL function. If so, we can use the CD function. According to the likelihood ratio test in Table 4.12 in Appendix 4.4, we can reject the null hypothesis of square and interaction terms are equal to zero. Therefore, the TL function (model (6)) is the best functional form. Hereafter, we use parameter estimates of model (6) to describe the main findings of this research.

Roo, Tabasco and Yucatan. PROCAMPO (TI equation): this is the coefficient of PROCAMPO in the (mean) Technical Efficiency equation for the corresponding sample.

Using the parameter estimates in model (6) and the JLMS formula in Jondrow et al. (1982),[170] we encounter that the ATE score is 46% (see Table 4.4). Farm-specific TE scores vary between 0.47% and 90.23% in these models. Other things equal and using sample means, Table 4.4 shows the elasticities of the corresponding inputs. These results show that we can reject the null hypothesis of constant RTS (sum of elasticities is 1) at the 1% significance level. Therefore, farms in the sample exhibit increasing RTS.[171]

**Table 4.3 Parameter estimates of the production frontier**

| Variables | *Frontier* | | | | | |
|---|---|---|---|---|---|---|
| | *Cobb-Douglas* | | | *Translog* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Capital* | 0.0245*** | 0.0178*** | 0.0172*** | 0.1417*** | 0.1164*** | 0.1204*** |
| | (0.0017) | (0.0016) | (0.0016) | (0.0179) | (0.0169) | (0.0169) |
| *Capital square* | | | | 0.0002 | 0.0015* | 0.0012 |
| | | | | (0.0009) | (0.0008) | (0.0008) |
| *Land* | 0.3523*** | 0.4136*** | 0.4156*** | 0.4129*** | 0.4229*** | 0.4253*** |
| | (0.0077) | (0.0077) | (0.0077) | (0.0633) | (0.0606) | (0.0609) |
| *Land square* | | | | -0.0935*** | -0.0941*** | -0.0936*** |
| | | | | (0.0041) | (0.0041) | (0.0041) |
| *Labour* | 0.1018*** | 0.0939*** | 0.0918*** | 0.1104* | 0.3108*** | 0.3008*** |
| | (0.0074) | (0.0071) | (0.0072) | (0.0630) | (0.0597) | (0.0606) |
| *Labour square* | | | | 0.0255*** | 0.0120*** | 0.0128*** |
| | | | | (0.0040) | (0.0038) | (0.0039) |
| *Inputs* | 0.6569*** | 0.5536*** | 0.5465*** | -0.0424 | -0.0018 | -0.0043 |
| | (0.0052) | (0.0057) | (0.0058) | (0.0482) | (0.0463) | (0.0466) |
| *Inputs square* | | | | 0.0657*** | 0.0552*** | 0.0549*** |
| | | | | (0.0020) | (0.0020) | (0.0021) |
| *Capital*Land* | | | | 0.0242*** | 0.0225*** | 0.0228*** |
| | | | | (0.0016) | (0.0016) | (0.0016) |
| *Capital*Labour* | | | | 0.0073*** | 0.0061*** | 0.0060*** |
| | | | | (0.0018) | (0.0016) | (0.0016) |
| *Capital*Inputs* | | | | -0.0223*** | -0.0203*** | -0.0205*** |
| | | | | (0.0013) | (0.0013) | (0.0013) |
| *Land*Labour* | | | | 0.0753*** | 0.0665*** | 0.0661*** |
| | | | | (0.0075) | (0.0071) | (0.0072) |
| *Land*Inputs* | | | | -0.0284*** | -0.0151*** | -0.0151*** |
| | | | | (0.0046) | (0.0046) | (0.0046) |
| *Labour*Inputs* | | | | -0.0610*** | -0.0570*** | -0.0569*** |
| | | | | (0.0054) | (0.0052) | (0.0052) |
| *Oxen* | -0.4586*** | -0.3931*** | -0.3864*** | -0.4200*** | -0.3652*** | -0.3622*** |
| | (0.0171) | (0.0173) | (0.0174) | (0.0167) | (0.0169) | (0.0170) |
| *Constant* | 2.9033*** | 4.1287*** | 4.2659*** | 5.9658*** | 5.6361*** | 5.7669*** |
| | (0.0707) | (0.0816) | (0.0850) | (0.3690) | (0.3522) | (0.3572) |
| Observations | 33,721 | 33,721 | 33,721 | 33,721 | 33,721 | 33,721 |
| Log-likelihood | -53495 | -52288 | -52226 | -52537 | -51533 | -51489 |
| Fixed effects (regions) | Yes | Yes | Yes | Yes | Yes | Yes |
| Inefficiency effects (mean) | No | Yes | Yes | No | Yes | Yes |
| Inefficiency effects (variance) | No | No | Yes | No | No | Yes |
| Subsidy variable (Dummy) | No | Yes | Yes | No | Yes | Yes |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[170] Technical efficiency via: $TE = \exp(-E(u|e))$.
[171] We cannot reject the null hypothesis of sum of elasticities equal 1.14 in model (6) at the 1% significance level.

Annual expenses on intermediate inputs (seeds, fertilisers, herbicides, etc.) are the main determinants of total output. A 1% rise in intermediate inputs increases total output by approximately 0.57%.[172] Such finding is in line with other studies (see for example Latruffe et al. 2017). These findings suggest that the allocation of one additional hectare of land[173] to (annual or seasonal) crops leads to a 1.56% rise in total output (at means). Among others, Zhu and Lansink (2010) and Giannakas et al. (2001) encounter a similar land-output elasticity in crop farms in Sweden (0.43) and wheat farms in Saskatchewan, Canada (0.44), respectively.

**Table 4.4 ATE, elasticities in the frontier, and returns to scale**

| | **Model (6)** |
|---|---|
| | **Average Technical Efficiency** |
| *Mean* | 45.80% |
| *SD* | 19.78% |
| *Range* | [0.47%-90.23%] |
| **Variable** | **Estimated elasticities (at means)** |
| *Capital* | 0.0165*** |
| | (0.0039) |
| *Land* | 0.4636 ** |
| | (0.0087) |
| *Labour* | 0.0889*** |
| | (0.0077) |
| *Inputs* | 0.5654*** |
| | (0.0063) |
| | **Returns to scale** |
| Null hypothesis: CRTS (Chi-2) | 170.15*** |
| Probability (Chi-2) | [0.0000] |
| Null hypothesis: IRTS (Chi-2) | 0.31 |
| Probability (Chi-2) | [0.5805] |

CRTS: Constant Returns to Scale (sum of elasticities equal 1)
IRTS: Increasing Returns to Scale (sum of elasticities equal 1.08 CD and 1.14 TL)
*** p<0.01, ** p<0.05, * p<0.1

[172] One may argue that the aggregation of intermediate inputs in a single category assumes that the production process is separable. It implies that, for example, the marginal rate of technical substitution (MRTS) between seeds and fertilisers is independent of the number of tractors, working hours, and land. This assumption seems slightly unrealistic; however, we do not address this issue in this analysis and the reader may be aware of the implications of such assumption.

[173] One hectare represents 3.37% of the sample average (29.64 has).

Regarding labour, farmers need to spend or hire 672 additional working hours[174] on farming activities to increase total output by 1%. Hadley (2006) computed similar labour-output elasticities in England and Wales. Surprisingly, the capital-output elasticity is slightly small. Brümmer and Loy (2000) identified an output elasticity of capital of 0.049 in Northern Germany, which is similar to our results. We acknowledge that the capital variable suffers from measurement errors. The capital variable in this analysis differs from the ideal measure because we were unable to compute the cost of buildings and oxen[175] properly due to data limitations. Furthermore, some of the costs included in the intermediate inputs variable might be included in the capital variable. For instance, some farmers rented machinery, equipment, and/or facilities and these costs are part of the intermediate inputs variable. The costs of irrigation and debt are also included in the intermediate inputs variable. Therefore, the aforementioned accounting deficiencies of the capital variable influence the size of the corresponding elasticity.

### *4.4.2. Technical inefficiencies*

The TI equation uses the JLMS estimator of $u_i$ in equations (4.9) and (4.10) as dependent variable. Table 4.5 shows the parameter estimates of inefficiency effects. Regardless of the functional form of the frontier, all coefficients are in line with our initial expectations. Since *age* of the farmer proxies experience in farming activities, the negative sign on the associated coefficient indicates that older farmers are more efficient than young agriculturalists. This finding is in line with previous estimations (e.g. Coelli and Batesse, 1996). More *years of schooling* may improve farmers' abilities to acquire knowledge related to farming activities, especially to avoid waste of resources. The corresponding coefficient on education suggests that additional years of schooling reduce technical inefficiencies. This result further support

[174] It represents 11% of the current sample mean.
[175] Although 20% of the farms in the sample use oxen, the NAS-2014 only collects information on whether the farm uses oxen or not rather than the frequency of using animal power or the number of oxen.

the view of education contributes to the efficient allocation of resources and the optimal use of existing technology (Sotnikov, 1998; Dinar et al., 2007).

Parameter estimates of the TI equation reveal that the ratio of *owned area* to total farmland shrinks the gap between the current output and the frontier. In this case study, borrowing, renting, or using land under the *'a medias'* scheme[176] leads to technical inefficiencies. Rezitis et al. (2003) argue that renting land increases TE but we do not encounter evidence in favour of such conjecture. Such finding might be an indication that farmers renting or borrowing land exhaust the properties (fertility) of land and therefore, such fields are less productive. In addition to the previous argument, farmers with borrowed or rented land might not have or have fewer incentives to invest in improvements in the soil. *Hiring labour* incentivises farmers to operate closer to the frontier. This effect contradicts the hypothesis that family labour is better skilled or more involved in farming activities than hired labour (Zhu and Lansink, 2010). Thus, the pressure for clearing labour costs forces farmers to be more efficient.

*Specialisation* alienates farmers from the frontier. The associated coefficient to the Herfindahl index indicates that higher proportions of land allocated to the production of a single crop increases TIs. Such a finding suggests that benefits from diversification exceed benefits from specialisation. The standard assumption that specialisation boosts efficiency does not hold (Latruffe et al., 2011). In line with the initial expectations, as the ratio of *irrigated area* to total farmland increases, TI goes down. Since the share of irrigated land is an indicator of land with unreliable rainfall, this effect captures to what extent famers can cope with shortages of water by replacing rainfall with irrigation (Karagiannis and Sarris, 2002).

The associated coefficients to the *abroad* variable are not statistically different from zero. It is been argued in the literature that farms selling some of the produce abroad tend to use resources

[176] Agreement between landowners and farmers in which both parts split production costs and total revenue (or losses) in halves.

more efficiently due to high competition in such markets. Surprisingly, we do not encounter evidence supporting this argument. There are few farms in Mexico selling their products abroad directly. Most producers sell raw products to intermediaries and food processors, who finally export such agricultural commodities to the USA and other markets. Unfortunately, the NAS survey does not collect information to track the final destination of agricultural commodities. Therefore, the fact that we do not observe whether the farm is somehow linked to the external market or not, unless the farmer sells some of the produce abroad directly, might lead to non-significant results.

The SFA model identifies a negative *subsidy*-TE link in crop farms in Mexico. The negative association is consistent under various specifications of the SFA model. The subsidisation programme indirectly pushes farmers to operate further away from the maximum attainable output. Such result suggests that PROCAMPO discourages farmers' to use available resources more efficiently in order to obtain higher revenues. PROCAMPO subsidy payments might compensate low-income farmers, and then such farmers put less effort on farming activities. This indicates that in average recipients do not use available inputs optimally, which leads to higher inefficiencies.

Interestingly, parameter estimates of the variance TI equation in Table 4.5 indicate that PROCAMPO reduces production uncertainty, that is, the variance of TI (Wang, 2002). As other investors, farmers invest in different types of inputs hoping to earn enough from selling their outputs to cover the cost of such inputs. By doing this, they will earn some profits. If the farmer invests in the production of risky crops, the cost of such risk (production uncertainty) is very high because of the high probability of losing the investment. Thus, farmers will not make such investments unless the payback will be large enough to compensate them for taking the risk of losing the investment. There is a trade-off between risk and returns. Under such circumstances, PROCAMPO ensures a certain portion of farmers' income and therefore, reduces the incentive to look for higher revenues by investing on the production of risky crops. We also encounter empirical evidence in favour of the standard assumption that specialisation increases production uncertainty (risk). The associated coefficient to the Herfindahl index in the variance TI equation suggests that as diversification of crops increases (lower values of the Herfindahl index) the variance of TI goes down. As expected, irrigation also reduces uncertainty in the production of crops.

**Table 4.5 Parameter estimates of the inefficiency effects model**

| Variables | *Technical inefficiency (mean)* *Translog* | Variables | *Technical inefficiency (variance)* *Translog* |
|---|---|---|---|
| | **(6)** | | **(6)** |
| *Age* | -0.0078*** | *Age* | 0.0051*** |
| | (0.0029) | | (0.0019) |
| *Schooling* | -0.0734*** | *Schooling* | 0.0205*** |
| | (0.0119) | | (0.0062) |
| *Owned area* | -0.1171*** | *Owned area* | 0.0836*** |
| | (0.0211) | | (0.0153) |
| *Hired labour* | -0.2851*** | *Hired labour* | 0.0213 |
| | (0.0387) | | (0.0181) |
| *Herfindahl* | 1.0188** | *Herfindahl* | 0.4884* |
| | (0.4107) | | (0.2518) |
| *Irrigated area* | -0.4545*** | *Irrigated area* | -0.0268 |
| | (0.0550) | | (0.0192) |
| *Abroad* | 0.5321 | *Abroad* | -0.3316 |
| | (0.7926) | | (0.4275) |
| *Procampo (dummy)* | 0.7109*** | *Procampo (dummy)* | -0.2732*** |
| | (0.0906) | | (0.0544) |
| *Constant* | 0.9965*** | | |
| | (0.3546) | | |
| *Vsigma_constant* | -0.2547*** | *Usigma_constant* | -0.4798** |
| | (0.0182) | | (0.2381) |
| *E(sigma_u)* | 1.2633 | *Sigma_v* | 0.8804*** |
| | | | (0.0080) |
| Observations | | 33,721 | |
| Log-likelihood | | -51489 | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Before we analyse observation-specific marginal effects from the single-step estimation, let us examine the marginal effects along the entire distribution of TI using RIF-regressions. Using the JLMS formula in equation (4.8) and parameter estimates in Table 4.3, we compute the values of the predicted values of the non-negative error term $\widehat{u_i}$. Figure 4.4 displays the results of the RIF-regressions for each percentile of the TI distribution[177] in the TL model respectively. The horizontal axis indicates the percentile of the predicted non-negative error term ($\widehat{u_i} = -\ln TE_i$). Thus, the closer to zero the more efficient the farm is. The vertical axis measures the marginal effect (coefficient associated to PROCAMPO in the RIF-regression). To adjust standard errors, we use the bootstrapping method with 100 repetitions for each percentile-specific coefficient. Using the adjusted standard errors, dashed lines are the lower and upper limits of the 95% confidence intervals of the percentile-specific marginal effects.

Figure 4.4 suggest that the negative relationship between PROCAMPO and farms' TE is not the same for all farms. Interestingly, we encounter differential effects, that is, the size of the negative association between PROCAMPO and TI increases with TI. The marginal effect of the subsidy payments is larger for those farms that operate further away from the frontier. For example, Figure 4.4 shows that at the 10-th percentile, PROCAMPO increases TI by 3.70%. In contrast, at the 90-th percentile, PROCAMPO rises TI by 15.15%. Both figures show that the subsidy-TI link is not monotonic, which also justifies the use of Wang's model.

Turning now to the observation-specific association of PROCAMPO and farms' TE, we use equation (4.11), to compute such effects. Table 4.6 displays the distribution of marginal effects of all variables in the mean TI equation. On average, and other things equal, one additional year of experience reduces TI by 0.02%. Taking the mean of the marginal effect, a 38 years old farmer is approximately 0.38% less efficient than a 57 years old agriculturalist.[178] Thus, experience on farming activities slightly reduce inefficiencies in the production process.

[177] The set of RIF-regressions uses the same model specification for the mean TI equation as in Table 4.5.
[178] Sample mean equals to 58 years.

**Figure 4.4 Percentile-specific marginal effects of PROCAMPO on technical inefficiency**

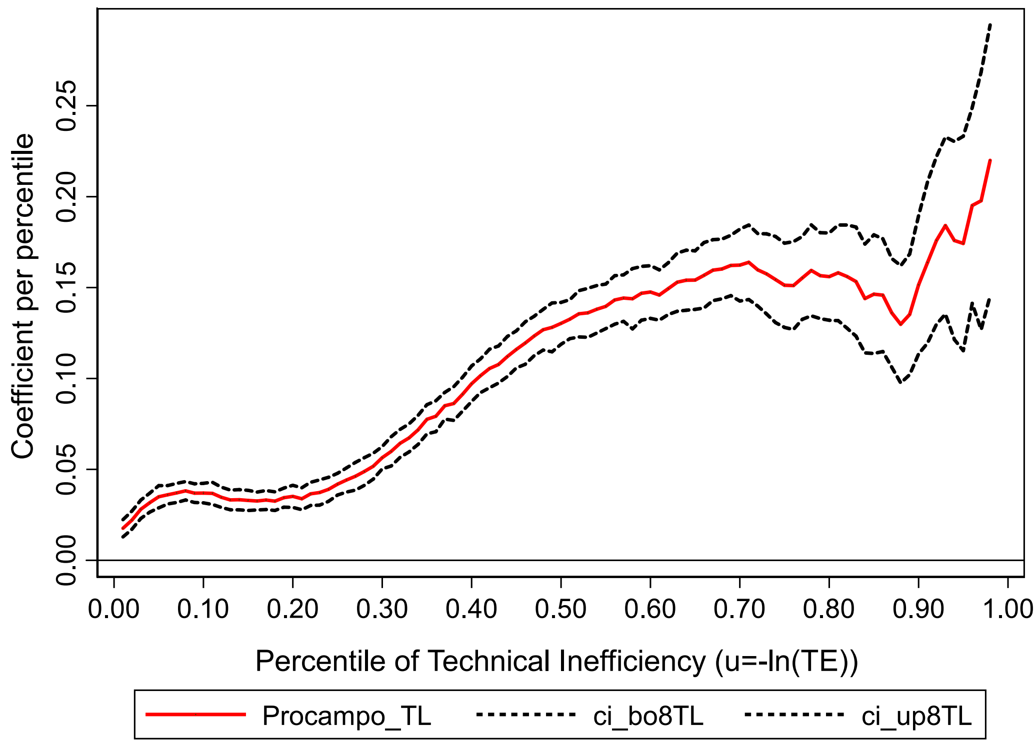



**Figure 4.4 Model (6)**

Note: the dependent variable is $\hat{u}_i = -\ln TE_i$ therefore, the closer to zero, the more efficient the farm is. The red line shows the coeffcicient associated to the PROCAMPO dummy variable in the mean TI equation at the corresponding percentile. Dotted lines are the 95% confidence intervals.

Regarding years of schooling, one more year of education improves the manner in which farmers use available resources and makes them 1.44-1.45% more efficient. Before 1993, primary school education was compulsory and free in Mexico.[179] These studies require 6 years of schooling (sample mean equals 6.13 years) thus most farmers in the sample were subject to such regulation. Since 1993, both primary and secondary education are compulsory and free. Therefore, one may expect that three additional years of (secondary) education of younger farmers will rise TE in the subsequent years by approximately 4.35%.

The TL model suggests that land ownership slightly reduces TI. Increasing the share of area-owned to total area by 10% reduces TI scores by -0.004% in average. Thus, buying or renting

[179] Most of the farmers born in 1956 and completed their studies before the 1993 reform.

land does not considerably improve the use of available resources. Holding other things fixed, if farmers increase the proportion of hired labour to total labour by 10%, TI diminishes by 0.83%. Using the mean of the corresponding variables, hiring an additional full-time worker or 253 *jornales* (2,024 working hours per annum) increases the proportion of hired labour to total labour from 24% to 58%. Consequently, such an adjustment leads to a reduction of 3% in TI scores. In this regard, further research is required to distinguish the size of the corresponding marginal effects between full-time workers, temporary workers and *jornaleros*.

Results in Table 4.6 suggest that a 1% increase in the degree of specialisation makes farmers 0.55% more inefficient. Currently, 75.54% of the 33,721 farms in the sample allocate all their land to a single commodity. This high degree of specialisation might be the reason for such an effect. To contextualise the size of the (average) marginal effect in Table 4.6, if an average farmer equally allocates his land to the production of two different crops (Herfindahl equals 0.50), we expect that this farmer would be 25-29% more efficient than a fully specialised farmer (Herfindahl index equals 1). Therefore, benefits from coping with production risks and selecting the most suitable crop for heterogeneous qualities of land (diversification) exceed benefits from specialisation. Such finding coincides with previous findings in the existing literature (Manjunatha et al., 2013; Manevska-Tasevska et al., 2013). Hazra (2000) argues that crop diversification can improve soil fertility if crops with different nutrient requirements benefit from the cultivation of the other ones. For instance, in Mexico, it is customary to cultivate beans and maize because the former fixes the Nitrogen in the soil, which is a nutrient requirement for the production of maize. By doing this, farmers become more efficient.

Table 4.6 also shows that installing an irrigation system in a rain-fed field, which is a 100% increase in the percentage of irrigated area, reduces the waste of resources and makes farmers 16% more efficient. We argue that this effect does not arise due to a misspecification of the frontier function since the cost of irrigation is part of the intermediate inputs variable. For some plants, water stimulates fertilisers and nutrients uptake therefore, the availability of irrigation is crucial since it guarantees the farmer can cope with water shortages form unreliable rainfall. Policy-makers should use this finding to design policies that facilitate the acquisition of irrigation equipment and infrastructure. Selling agricultural commodities abroad is not significant.

**Table 4.6 Marginal effects of variables in the technical inefficiency model**

| Variable | Model (6) Mean | Min. | Max. |
|---|---|---|---|
| *Age* | -0.0002 | -0.0073 | 0.0019 |
| *Schooling* | -0.0145 | -0.0704 | 0.0033 |
| *Owned area* | -0.0004 | -0.1103 | 0.0328 |
| *Hired labour* | -0.0827 | -0.2756 | -0.0120 |
| *Herfindahl* | 0.5490 | 0.1849 | 1.0071 |
| *Irrigated area* | -0.1591 | -0.4418 | -0.0368 |
| *Abroad* | 0.0234 | -0.1185 | 0.5030 |
| ***Procampo (dummy)*** | **0.1075** | **-0.0659** | **0.6787** |

Source: own elaboration based on inefficiency effects models and Wang (2002)

In average, PROCAMPO increases TI by 11% (see Table 4.6). To examine the distribution of observation specific-marginal effects, Figure 4.5 shows the relationship between TE scores (horizontal axis) and the observation-specific marginal effect of PROCAMPO on TI (vertical axis). The vertical (horizontal) dashed line is the ATE in Table 4.4 (zero line). From Table 4.6, we find that the subsidy-TI link alternate signs within the sample. This confirms the existence of differential effects of subsidy payments on TI encountered in the RIF-regressions. By simply looking at Figure 4.5, the positive effect of PROCAMPO on TI decreases as TE scores increases. Figure 4.4 shows similar results. However, using a more flexible specification of the SFA model, via Wang's model, we encounter that PROCAMPO reduces TI in some farms (farms below the zero line in Figure 4.5). According to model (6), 26.46% of the 33,721 farms in the sample are below the zero line in Figure 4.5, that is, these farms use PROCAMPO to improve TE.

**Figure 4.5 Marginal effects of PROCAMPO on technical inefficiency**

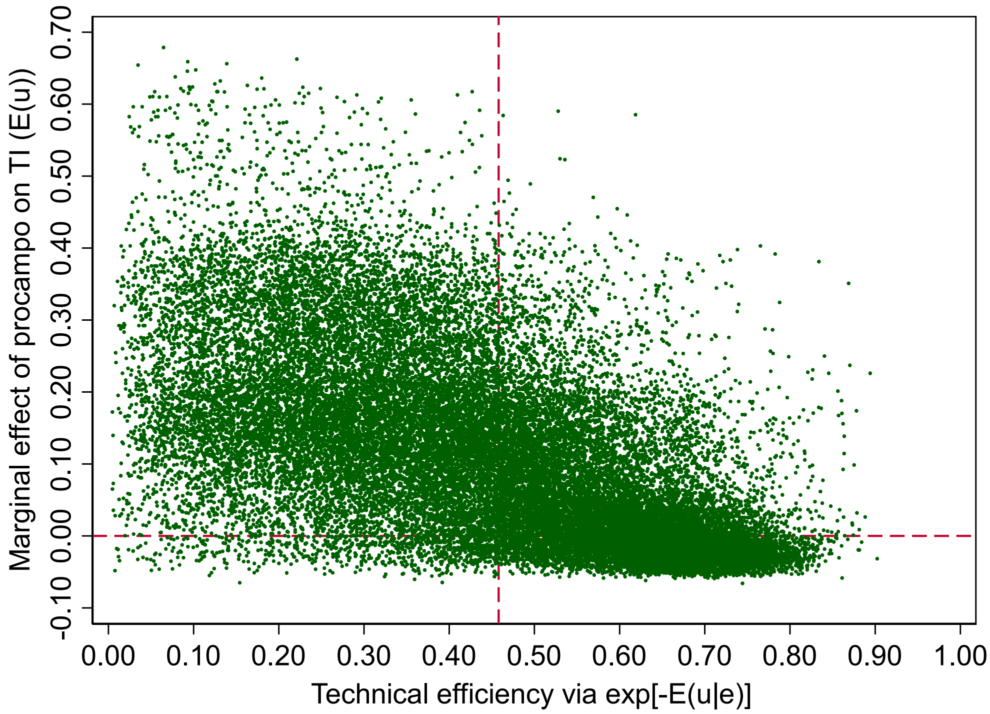



**Figure 4.5 Model (6): Translog**

Note: dots above (below) the zero line represent farms for which there is a positive (negative) PROCAMPO-TI association.

Model 6 suggests that PROCAMPO reduces (increases) TI by 2.25% (15.43%) in those farms below (above) the zero line, respectively. We notice that farms above the zero line use less capital, e.g. machinery and equipment, than those below the zero line ($37,974 versus $136,471 of average ownership cost of capital). Furthermore, 23.31% of farms with a positive PROCAMPO-TI relationship use oxen more frequently than farms with a negative subsidy-TI link (10.80%). Farms below the zero line are larger than other farms: 51 hectares versus 22 hectares of utilised land, 11,049 versus 4,145 working hours per annum and $642,069 versus $93,746 of annual expenses on intermediate inputs.[180]

[180] All these figures are the corresponding subsample means.

Regarding inefficiency effects, we do not observe significant differences in the age of the farmer and area-owned. However, farmers, who use PROCAMPO to increase TE, tend to be more educated than their counterparts (9.54 versus 4.90 years of schooling). Moreover, such farms hire more labour than other farms (51.27% versus 14.11% of total labour). In this regard, farms with a positive PROCAMPO-TI link tend to use more family labour than other farms, which the farmer cannot discipline easily. The degree of specialisation is slightly larger for farms above the zero line (Herfindahl index equals 0.92 versus 0.89). Farms with a positive PROCAMPO-TE association irrigate 82% of total farmland while other farms only irrigate 11% of the total area. Thus, policy-makers should reverse the negative association between PROCAMPO and TE by: (i) helping farmers to mechanise the production of crops, (ii) providing farmers with extension services (or education), (iii) facilitating the procedures to hire labour, (iv) incentivising crop diversification practices and (v) helping farmers to install irrigation facilities.

### *4.4.3. Robustness checks*

To verify the consistency of our findings and test for spillover effects of PROCAPO on farms with perennial and livestock activities, which were dropped from the sample, we conduct a set of additional estimations. Table 4.7 shows the size of the sample or subsample used in the corresponding SFA model, the distribution of ATEs, the coefficient associated to the PROCAMPO variable in the mean TI equation, and the distribution of observation-specific marginal effects of PROCAMPO on TI from the TL models. To be consistent with previous results, we use the same functional forms as in Tables 4.3 and 4.5.

To test for spillover effects of PROCAMPO, we estimate SFA models for farms that derive 100% of their production from both annual and/or perennial crops.[181] Overall, we do not

[181] Farms with some production of livestock are not included.

observe significant differences after including farms with perennial crops in the analysis. Aside from including the production of perennial crops, we estimate SFA models for different farm types. The existing literature uses the proportion of revenue attachable to a particular activity to classify farms. Most of the empirical analyses use a threshold of 2/3 of total revenue. Using this criterion, we estimate SFA models for all, beef cattle, arable, mixed, and pigs farms. We encounter strongly significant effects of PROCAMPO on farms' TI in the entire sample and the subsample of arable farms. However, for non-arable activities such an effect is not significant. Some of these farms might receive the subsidy since at most 1/3 of total revenues comes from arable activities. Under such circumstances, the subsidy might not be enough to influence TI at the farm-level. This also apply to mixed farms, which derive less than 2/3 of revenue from arable activities, and therefore the quantity of land they can enrol in PROCAMPO might not be sufficiently large to influence TI.

Testing for the robustness of parameter estimates using data on farms with 100% of their produce form annual crops, we examine whether the subsidy-TI link varies among farm size. We split the sample of annual crops into small, medium, and large-sized farms. The former type comprises those farms with less than or 5 hectares of land. Medium-sized farms utilise more than 5 hectares and less than 20 hectares of land. Large farms use 20 or more than 20 hectares of land. Table 4.7 suggests that the parameter associated to the PROCAMPO variable in the mean TI equation is always positive. Nonetheless, observation-specific marginal effects vary among farm sizes. For instance, PROCAMPO reduces TI in some small farms. Such finding suggests that scarcity of resources forces small farms to use inputs more efficiently (see for example Helfand and Levine (2004)). The PROCAMPO-TI relationship is not statistically significant for irrigated farms. However, we encounter a significant subsidy-TI relationship in rain-fed farms. In this regard, rain-fed farms receiving PROCAMPO are in average 13% less efficient than rain-fed farms without the subsidy.

Some studies such as Chavas et al. (2005) and Lambarraa et al., (2007) argue that farmsteads located in less developed areas (LFAs) face labour market rigidities and technology constraints, which reduce TE. However, in a recent study, Baráth et al. (2018) encounter that TE scores of LFA farms and non-LFA farms are not statistically different in Slovenian farms. In this regard, we identify farms situated within a LFA using the municipality-level marginalisation index released by the National Council of Population (CONAPO by its acronym in Spanish) in Mexico. Table 4.7 shows the results from the corresponding SFA models. The CD and the TL models suggest that LFA farms are in average less efficient than non-LFA farms in Mexico. According to the parameter estimates from the TI equation, LFA farms receiving the subsidy are in average 12% less efficient than other LFA farms. For non-LFA farms, beneficiaries are in average 7% less efficient than those farms without the subsidy. Thus, less efficient farms, which are typically situated in LFAs, observe a stronger negative PROCAMPO-TE association.

To better understanding the PROCAMPO-TE relationship, we estimate a SFA for each of the eight regions defined in subsection 4.4.1. Table 4.7 shows that farms in the South West region are less efficient than farms situated in other regions. Such a finding is in line with the previous result since most of the LFAs belong to Chiapas, Guerrero and Oaxaca, which are the three poorest states in Mexico. On the other hand, we encounter that farms that are more efficient can be found at northern and western Mexico. The linkage between farms within such regions and the US market partly explains the higher farms' TE scores. Moreover, the SFA models indicate that there exist a positive subsidy-TE link in regions other than northern Mexico, where we find non-significant results.[182]

[182] Although the CD model finds a statistically significant negative PROCAMPO-TE association, the Log-Likelihood ratio test indicates that the TL should be preferred.

# Table 4.7 Robustness checks

| Model/sample | Obs. | ATE | | | Model (6) PROCAMPO | Marginal effect | | |
|---|---|---|---|---|---|---|---|---|
| | | Mean | Min. | Max. | (TI equation) | Mean | Min. | Max. |
| **Annual and perennial crops** | | | | | | | | |
| *Annual crops* | 33,721 | 45.80% | 0.47% | 90.23% | 0.7109*** | 0.11 | -0.07 | 0.68 |
| *Annual and perennial* | 36,719 | 44.71% | 0.50% | 90.11% | 0.6675*** | 0.10 | -0.08 | 0.65 |
| **Farm types** | | | | | | | | |
| *All farms* | 56,529 | 50.50% | 0.56% | 90.18% | 0.7208*** | 0.05 | -0.08 | 0.60 |
| *Beef cattle* | 5,792 | 9.41% | 4.03% | 28.14% | 0.0244 | 0.13 | 0.13 | 0.13 |
| *Arable* | 46,300 | 48.55% | 0.57% | 90.01% | 0.6817*** | 0.08 | -0.09 | 0.65 |
| *Mixed* | 3,908 | 64.60% | 0.83% | 91.28% | 1.0424 | 0.01 | -0.01 | 0.91 |
| *Pigs* | 529 | 37.96% | 2.30% | 78.26% | -0.3697 | -0.10 | -0.37 | 0.15 |
| **Farm size** | | | | | | | | |
| *Small-sized (<=5 has)* | 13,994 | 27.27% | 3.47% | 81.81% | 0.2905*** | -0.75 | -10.80 | 0.29 |
| *Medium-sized (>5 & <20 has)* | 10,764 | 49.96% | 0.35% | 89.77% | 0.8540*** | 0.10 | -0.03 | 0.73 |
| *Large-sized (=>20 has)* | 8,963 | 48.67% | 0.04% | 91.54% | 0.4422* | 0.03 | -0.03 | 0.40 |
| **Irrigated and rain-fed farms** | | | | | | | | |
| *Irrigated* | 12,439 | 55.35% | 0.08% | 92.79% | 0.3243 | -0.02 | -0.04 | 0.32 |
| *Rain-fed* | 21,282 | 55.18% | 0.74% | 88.61% | 2.1352** | 0.13 | 0.02 | 1.00 |
| **Farms in LFAs and non-LFAs** | | | | | | | | |
| *LFAs* | 8,745 | 25.13% | 1.87% | 96.98% | 0.1397*** | 0.12 | 0.02 | 0.14 |
| *Non-LFAs* | 24,976 | 49.38% | 0.21% | 91.04% | 0.8493*** | 0.07 | -0.07 | 0.68 |
| **Farms in different regions** | | | | | | | | |
| *North West* | 4,874 | 54.34% | 0.07% | 92.52% | -0.0702 | -0.11 | -0.2 | -0.06 |
| *North East* | 2,828 | 52.60% | 1.16% | 92.22% | -0.7208 | -0.11 | -0.31 | -0.02 |
| *West* | 4,157 | 54.14% | 0.03% | 90.03% | 4.2847* | 0.10 | -0.14 | 1.36 |
| *East* | 6,472 | 41.07% | 3.49% | 99.60% | 0.2261*** | 0.21 | 0.01 | 0.23 |
| *Centre North* | 4,726 | 41.54% | 0.70% | 87.73% | 0.8167*** | 0.17 | -0.12 | 0.79 |
| *Centre South* | 3,309 | 45.48% | 14.51% | 99.86% | 0.2186*** | 0.20 | 0.001 | 0.22 |
| *South West* | 4,577 | 34.52% | 21.33% | 94.98% | 0.0578 | 0.03 | -2.78 | 0.06 |
| *South East* | 2,778 | 36.90% | 0.53% | 85.39% | 0.9205*** | 0.36 | 0.04 | 0.92 |

Annual crops: at least 2/3 of total revenue comes from annual crops. Annual crops and perennial crops: at least 2/3 of total revenue comes from annual and perennial crops.
All farms: all farms with complete information in the 2014 NAS. Beef cattle, arable and pigs farm types: at least 2/3 of total revenue comes from the corresponding type. Mixed: any of the activities account for 2/3 of total revenue.
Rain-fed farms: farms with share of irrigated area to total area equals zero. Irrigated farms: farms with share of irrigated area to total area greater than zero.
LFAs (Non-LFAs): farms located in a (non) Less Favoured Area. We use the municipality-level CONAPO's marginalisation index to identify LFAs.
Nort West: Baja California, Baja California Sur, Chihuahua, Durango, Sinaloa and Sonora. Nort East: Coahuila, Nuevo Leon and Tamaulipas. West: Colima, Jalisco, Michocan and Nayarit.
East: Hidalgo, Puebla, Tlaxcala and Veracruz. Centre North: Aguascalientes, Guanajuato, Queretaro, San Luis Potosi and Zacatecas. Centre South: CDMX, Estado de Mexico and Morelos.
South West: Chiapas, Guerrero and Oaxaca. South East: Campeche, Quintana Roo, Tabasco and Yucatan.
PROCAMPO (TI equation): this is the coefficient of PROCAMPO in the (mean) Techincal Efficiency equation for the corresponding sample.
*** p<0.01, ** p<0.05, * p<0.1

Looking at ATE scores in Table 4.7, one can observe that these scores vary among farm types, farm size, the availability of irrigation, LFA and non-LFAs, and regions. Mixed farms tend to be more efficient than other farm types. Such result support the previous finding about the positive effect of diversification on TE. Farms producing beef cattle have the lowest ATE scores. There are two potential explanations for such finding. First, the production of beef cattle mainly relies on extensive practices in Mexico therefore larger quantities of land appear in the frontier function. Second, the time at which revenues from this type of farm become apparent does not necessarily coincide with the 2014 agricultural year. Thus, total output reported in the NAS might be below the actual output. Moreover, we use the same measure of capital as in the main SFA estimation, which is not a correct measure of capital endowments for beef cattle farms. Interestingly, we encounter that medium-sized farms tend to be more efficient than small and large farms, which suggests that the optimal size of crop farms is within the 5-20 hectares range. Further investigation is needed to confirm such result. As expected, irrigated farms are slightly more efficient than rain-fed farms.

## 4.5. Conclusions

Using the stochastic frontier approach and cross-sectional data on 33,721 that obtain 100% of their output from annual crops, this research investigates the association between PROCAMPO subsidy payments and farms' technical efficiency in Mexico. This study contributes to the existing literature by providing empirical evidence on the link between agricultural subsidies and TE in a large middle income country where there is no prior evidence concerning any such relationship and computing observation-specific and percentile-specific marginal effects of subsidy payments on TI using Wang's formula and RIF-regressions respectively. Wang's formula and the set of RIF-regressions allow us to examine different PROCAMPO-TI associations within the sample, which has not been explored in previous studies.

This investigation uses a dummy variable indicating whether the farmer receives the subsidy or not in order to identify the subsidy-TI link. The main findings suggest that: i) the average technical efficiency in the 33,721 crop farms is between 43% and 46%; ii) the negative effect of PROCAMPO on farms' TE increases as technical inefficiency rises; iii) according to the CD and TL models, PROCAMPO negatively influences farms' TE in 68.52% and 73.54% of farms in the sample respectively (positive effects in the remaining farms); and iv) age, years of schooling, area-owned, hired labour, diversification and irrigation increase TE scores.

The estimation of farms' TE scores and the examination of inefficiency effects become relevant since policy-makers should re-evaluate the effectiveness of public policies on farms' performance. Looking at the characteristics of those farms with a positive subsidy-TE relationship, policy-makers should contribute to the mechanisation of production of crops, provide farmers with extension services, facilitate the procedure to hire labour, incentivise crops diversification and help farmers to install irrigation facilities. Furthermore, policy-makers should re-formulate the allocation criteria of the subsidisation programme, which may not be suitable for the current context, e.g. subsidies linked to the level of TE.

To interpret the set of findings in this research the reader should be aware of the following caveats. First, TE (TI) scores of crop farms may be upward (downward) biased because the ownership cost of buildings is not accounted for in the frontier model. Second, some farms might put more land into cultivation in order to enrol their lands into the subsidisation programme. These fields appear in the frontier equation and might cause some biases in the non-negative error term. Further steps of this research should account for endogeneity issues since some of the inputs in the frontier equation might be correlated with stochastic events, which are usually part of the error term.

## References


Aigner, D., Lovell, C.K. and Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. *Journal of econometrics*, *6*(1), pp.21-37.

Amara, N., Traoré, N., Landry, R. and Remain, R., 1999. Technical efficiency and farmers' attitudes toward technological innovation: The case of the potato farmers in Quebec. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *47*(1), pp.31-43.

Anania, G. and D'Andrea, M.R.P., 2015. The 2013 Reform of the Common Agricultural Policy. *The Political Economy of the 2014-2020 Common Agricultural Policy: An Imperfect Storm*, pp.33-86.

Bandyopadhyay, D. and Das, A., 2006. On measures of technical inefficiency and production uncertainty in stochastic frontier production model with correlated error components. *Journal of Productivity Analysis*, *26*(2), pp.165-180.

Baráth, L., Fertő, I. and Bojnec, Š., 2018. Are farms in less favored areas less efficient?. *Agricultural Economics*, *49*(1), pp.3-12.

Battese, G.E. and Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical economics*, *20*(2), pp.325-332.

Bojnec, S. and Ferto, I., 2011, August. Impact of off-farm income on farm efficiency in Slovenia. In *Congress of the European Association of Agricultural Economists. Zurich, Switzerland*.

Bojnec, Š. and Latruffe, L., 2009. Determinants of technical efficiency of Slovenian farms. *Post-Communist Economies*, *21*(1), pp.117-124.

Borah, B.J. and Basu, A., 2013. Highlighting differences between conditional and unconditional quantile regression approaches through an application to assess medication adherence. *Health economics*, *22*(9), pp.1052-1070.

Boyd, T., Docken, G. and Ruggiero, J., 2016. Outliers in data envelopment analysis. *Journal of Centrum Cathedra*, *9*(2), pp.168-183.

Brümmer, B. and Loy, J.P., 2000. The technical efficiency impact of farm credit programmes: A case study of Northern Germany. *Journal of Agricultural Economics*, *51*(3), pp.405-418.

Carroll, J., Greene, S., O'Donoghue, C., Newman, C.F. and Thorne, F.S., 2009, April. Productivity and the determinants of efficiency in Irish agriculture (1996-2006). In *83rd Annual Conference, March 30-April 1, 2009, Dublin, Ireland* (No. 50941). Agricultural Economics Society.

Caudill, S.B. and Ford, J.M., 1993. Biases in frontier estimation due to heteroscedasticity. *Economics Letters*, *41*(1), pp.17-20.

Caudill, S.B., Ford, J.M. and Gropper, D.M., 1995. Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business & Economic Statistics*, *13*(1), pp.105-111.

Chambers, R. G., 1988. *Applied production analysis: a dual approach.* Cambridge University Press.

Charnes, A., Cooper, W.W. and Rhodes, E., 1978. Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), pp.429-444.

Chavas, J.P., Petrie, R. and Roth, M., 2005. Farm household production efficiency: evidence from the Gambia. *American Journal of Agricultural Economics*, *87*(1), pp.160-179.

Christensen, L.R., Jorgenson, D.W. and Lau, L.J., 1973. Transcendental logarithmic production frontiers. *The review of economics and statistics*, pp.28-45.

Coelli, T.J. and Battese, G.E., 1996. Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economics*, *40*(2), pp.103-128.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J. and Battese, G.E., 2005. *An introduction to efficiency and productivity analysis*. Springer Science & Business Media.

Cooper, W.W., Seiford, L.M. and Zhu, J., 2011. Data envelopment analysis: History, models, and interpretations. In *Handbook on data envelopment analysis* (pp. 1-39). Springer, Boston, MA.

Dinar, A., Karagiannis, G. and Tzouvelekas, V., 2007. Evaluating the impact of agricultural extension on farms' performance in Crete: a nonneutral stochastic frontier approach. *Agricultural Economics*, *36*(2), pp.135-146.

DOF, 1994. Decreto que regula el Programa de Apoyos Directos al Campo denominado PROCAMPO. *Diario Oficial de la Federación.* México, DF. 25 de Julio de 1994.

DOF, 2013. ACUERDO por el que se dan a conocer las Reglas de Operación de los Programas de la Secretaría de Agricultura, Ganadería, Desarrollo Rural, Pesca y Alimentación. *Diario Oficial de la Federación.* México, DF. 11 de Febrero de 1994.

Douglas, P.C. and Cobb, C.W., 1928. A theory of production. *The American Economic Review*, *18*(1), pp.139-165.

Dung, K.T., Sumalde, Z.M., Pede, V.O., McKinley, J.D., Garcia, Y.T. and Bello, A.L., 2011. Technical Efficiency of Resource-Conserving Technologies in Rice-Wheat Systems: The Case of Bihar and Eastern Uttar Pradesh in India. *Agricultural Economics Research Review*, *24*(2).

Edwards, W. M., 2015. Estimating farm machinery costs. Cooperative Extension Service, Iowa State University.

Farrell, M. J., 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), pp. 253-290.

Foster, W.E. and Rausser, G.C., 1991. Farmer behavior under risk of failure. *American Journal of Agricultural Economics*, *73*(2), pp.276-288.

García-Salazar, J.A., Skaggs, R. and Crawford, T.L., 2011. PROCAMPO, the Mexican corn market, and Mexican food security. *Food Security*, *3*(3), p.383.

Giannakas, K., Schoney, R. and Tzouvelekas, V., 2001. Technical efficiency, technological change and output growth of wheat farms in Saskatchewan. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *49*(2), pp.135-152.

González-Konig, G. and Wodon, Q., 2005. Do cash transfers to farmers reduce migration? Procampo in Mexico. *No. EC200501, Department of Economics and Finance Working Papers, Universidad de Guanajuato. http://econpapers. repec. org/paper/guawpaper/ec200501. htm*.

Greene, W., 2012. *Econometric Analysis, 7th Edition*, Prentice Hall, Englewood Cliffs.

Greene, W.H., 2008. The econometric approach to efficiency analysis. *The measurement of productive efficiency and productivity growth*, *1*(1), pp.92-250.

Hadley, D., 2006. Patterns in technical efficiency and technical change at the farm-level in England and Wales, 1982–2002. *Journal of Agricultural Economics*, *57*(1), pp.81-100.

Hadri, K., 1999. Estimation of a doubly heteroscedastic stochastic frontier cost function. *Journal of Business & Economic Statistics*, *17*(3), pp.359-363.

Hallam, D. and Machado, F., 1996. Efficiency analysis with panel data: A study of Portuguese dairy farms. *European review of agricultural economics*, *23*(1), pp.79-93.

Halter, A.N., Carter, H.O. and Hocking, J.G., 1957. A Note on the Transcendental Production Function cx 1 a 1 e b 1 x 1 x 2 a 2 e b 2 x 2. *Journal of Farm Economics*, pp.966-974.

Hazra, C.R., 2000. Crop diversification in India. *Crop diversification in the Asia-Pacific Region.(Minas K. Papademetriou and Frank J. DentEds.). Food and Agriculture Organization ofthe United Nations. Regional Office for Asiaand the Pacific, Bangkok, Thailand*, pp.32-50.

Helfand, S.M. and Levine, E.S., 2004. Farm size and the determinants of productive efficiency in the Brazilian Center-West. *Agricultural economics*, *31*(2-3), pp.241-249.

Iraizoz, B., Bardaji, I. and Rapun, M., 2005. The Spanish beef sector in the 1990s: impact of the BSE crisis on efficiency and profitability. *Applied Economics*, *37*(4), pp.473-484.

Ito, J., 2015. Diversification of agricultural production in China: Economic rationality of Crop choice under the producer subsidy program. *The Japanese Journal of Rural Economics*, *17*, pp.1-17.

Jondrow, J., Lovell, C.K., Materov, I.S. and Schmidt, P., 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of econometrics*, *19*(2-3), pp.233-238.

Justyna, G., 2015. Subsidies and Technical Efficiency of Large-Scale Farms in Poland. In *Agrarian Perspectives XXIV. Global Agribusiness and the Rural Economy, Proceedings of the 24th International Scientific Conference, 16-18 September 2015, Prague, Czech Republic* (pp. 135-144). Czech University of Life Sciences Prague, Faculty of Economics and Management.

Karagiannis, G. and Sarris, A., 2002. Direct subsidies and technical efficiency in Greek agriculture. *Zaragoza (Spain)*, *28*, p.31.

Karagiannis, G. and Sarris, A., 2005. Measuring and explaining scale efficiency with the parametric approach: the case of Greek tobacco growers. *Agricultural Economics*, *33*, pp.441-451.

Karagiannis, G. and Tzouvelekas, V., 2005. Explaining output growth with a heteroscedastic non-neutral production frontier: the case of sheep farms in Greece. *European Review of Agricultural Economics*, *32*(1), pp.51-74.

Kumbhakar, S. C., Wang, H. J., and Horncastle, A. P., 2015. *A practitioner's guide to stochastic frontier analysis using Stata*. Cambridge University Press.

Kumbhakar, S.C. and Lien, G., 2010. Impact of subsidies on farm productivity and efficiency. In *The Economic Impact of Public Support to Agriculture* (pp. 109-124). Springer, New York, NY.

Kumbhakar, S.C. and Lovell, C.K., 2003. *Stochastic frontier analysis*. Cambridge university press.

Kumbhakar, S.C., Ghosh, S. and McGuckin, J.T., 1991. A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business & Economic Statistics*, *9*(3), pp.279-286.

Kumbhakar, S.C., Tsionas, E.G. and Sipiläinen, T., 2009. Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. *Journal of Productivity Analysis*, *31*(3), pp.151-161.

Lakner, S. and Breustedt, G., 2017. Efficiency Analysis of Organic Farming Systems–A Review of Concepts, Topics, Results and Conclusions. *German Journal of Agricultural Economics*, *66*(2), pp.85-108.

Lambarraa, F. and Kallas, Z., 2009. Subsidies and technical efficiency: An application of stochastic frontier and Random-effect Tobit models to LFA Spanish olive farms. In *The 113th EAAE seminar: A resilient European food industry and food chain in a challenging world*.

Lambarraa, F., Serra, T. and Gil, J.M., 2007. Technical efficiency analysis and decomposition of productivity growth of Spanish olive farms. *Spanish Journal of Agricultural Research*, *5*(3), pp.259-270.

Latruffe, L., Bakucs, L., Bojnec, S., Ferto, I., Fogarasi, J., Gavrilescu, C., Jelinek, L., Luca, L., Medonos, T. and Toma, C., 2008. Impact of public subsidies on farms' technical efficiency in New Member States before and after EU accession. *ratio*, *3*, pp.3-24.

Latruffe, L., Bravo-Ureta, B., Moreira, V.H., Desjeux, Y. and Dupraz, P., 2011, August. Productivity and subsidies in European Union countries: An analysis for dairy farms using input distance frontiers. In *EAAE 2011 International Congress* (Vol. 30).

Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y. and Moreira, V.H., 2017. Subsidies and technical efficiency in agriculture: Evidence from European dairy farms. *American Journal of Agricultural Economics*, *99*(3), pp.783-799.

Mamardashvili, P. and Schmid, D., 2013. Performance of Swiss dairy farms under provision of public goods. *Agricultural Economics (Czech)*, *59*(7), pp.300-314.

Manevska-Tasevska, G., Rabinowicz, E. and Surry, Y., 2013. Policy impact on farm level efficiency in Sweden 1998-2008. *Policy Impact on Farm Level Efficiency in Sweden: 1998–2008*.

Manjunatha, A.V., Anik, A.R., Speelman, S. and Nuppenau, E.A., 2013. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. *Land Use Policy*, *31*, pp.397-405.

Martin, J.P. and Page, J.M., 1983. The impact of subsidies on X-efficiency in LDC industry: theory and an empirical test. *The Review of Economics and Statistics*, pp.608-617.

McCloud, N. and Kumbhakar, S.C., 2008. Do subsidies drive productivity? A cross-country analysis of Nordic dairy farms. In *Bayesian Econometrics* (pp. 245-274). Emerald Group Publishing Limited.

Meeusen, W. and van Den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International economic review*, pp.435-444.

Minviel, J.J. and Latruffe, L., 2013. Explaining the impact of public subsidies on farm technical efficiency: Analytical challenges and Bayesian meta-analysis. *2013; 7. Journées de recherches en sciences sociales (JRSS), Angers, FRA, 2013-12-12-2013-12-13,*.

Minviel, J.J. and Latruffe, L., 2014, August. Meta-regression analysis of the impact of agricultural subsidies on farm technical efficiency. In *presentation at the EAAE 2014 Congress 'Agri-Food and Rural Innovations for Healthier Societies', August* (Vol. 26).

Minviel, J.J. and Latruffe, L., 2017. Effect of public subsidies on farm technical efficiency: a meta-analysis of empirical results. *Applied Economics*, *49*(2), pp.213-226.

Niroula, G.S. and Thapa, G.B., 2005. Impacts and causes of land fragmentation, and lessons learned from land consolidation in South Asia. *Land use policy*, *22*(4), pp.358-372.

Pechrova, M., 2013. Efficiency of biodynamic farms. Czech University of Life Science Prague.

Quiroga, S., Suarez, C., Fernandez-Haddad, Z. and Philippidis, G., 2017. Levelling the playing field for European Union agriculture: Does the Common Agricultural Policy impact homogeneously on farm productivity and efficiency?. *Land Use Policy*, *68*, pp.179-188.

Rasmussen, S., 2010. Scale efficiency in Danish agriculture: an input distance–function approach. *European Review of Agricultural Economics*, *37*(3), pp.335-367.

Reifschneider, D. and Stevenson, R., 1991. Systematic departures from the frontier: a framework for the analysis of firm inefficiency. *International economic review*, pp.715-723.

Rezitis, A.N., Tsiboukas, K. and Tsoukalas, S., 2003. Investigation of factors influencing the technical efficiency of agricultural producers participating in farm credit programs: The case of Greece. *Journal of Agricultural and Applied Economics*, *35*(3), pp.529-541.

Ruiz-Arranz, M., Davis, B., Stampini, M., Winters, P. and Handa, S., 2002. More calories or more diversity? An econometric evaluation of the impact of the PROGRESA and PROCAMPO transfer programs on food security in rural Mexico. *Documento de trabajo*, (02-09).

Sadoulet, E., De Janvry, A. and Davis, B., 2001. Cash transfer programs with income multipliers: PROCAMPO in Mexico. *World development*, *29*(6), pp.1043-1056.

Samarajeewa, S., Hailu, G., Jeffrey, S.R. and Bredahl, M., 2012. Analysis of production efficiency of beef cow/calf farms in Alberta. *Applied Economics*, *44*(3), pp.313-322.

Sauer, J., Park, T. and Graversen, J., 2007, September. Organic Farming in Denmark–Productivity, technical change and market exit. In *presentation at the 47th annual conference of the GEWISOLA and the 17th annual conference of the ÖGA*.

Scott-Andretta, J. and Cuecuecha, A., 2010. *The Effect of Agricultural Subsidies on Migration and Agricultural Employment* (No. DTE 474).

Serra, T., Zilberman, D. and Gil, J.M., 2008. Farms' technical inefficiencies in the presence of government programs. *Australian Journal of Agricultural and Resource Economics*, *52*(1), pp.57-76.

Sotnikov, S., 1998. Evaluating the effects of price and trade liberalisation on the technical efficiency of agricultural production in a transition economy: The case of Russia. *European Review of Agricultural Economics*, *25*(3), pp.412-431.

Tan, S., Heerink, N. and Qu, F., 2006. Land fragmentation and its driving forces in China. *Land use policy*, *23*(3), pp.272-285.

Tian, W. and Wan, G.H., 2000. Technical efficiency and its determinants in China's grain production. *Journal of productivity analysis*, *13*(2), pp.159-174.

Tleubayev, A., Bobojonov, I., Götz, L., Hockmann, H. and Glauben, T., 2017. *Determinants of productivity and efficiency of wheat production in Kazakhstan: A stochastic frontier approach* (No. 160). Discussion Paper, Leibniz Institute of Agricultural Development in Transition Economies.

Wang, H. J. (2002). Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis*, 18(3), 241-253.

Wang, H. J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis*, 18(2), 129-144.

Wheat, P., Stead, A. and Greene, W.H., 2018. Controlling for Outliers in Efficiency Analysis: A Contaminated Normal-Half Normal Stochastic Frontier Model.

Zaeske, A., 2012. Aggregate Technical Efficiency and Water Use in US Agriculture.

Zellner, A. and Revankar, N.S., 1969. Generalized production functions. *The Review of Economic Studies*, *36*(2), pp.241-250.

Zhao, M., Yin, R., Yao, L. and Xu, T., 2015. Assessing the impact of China's sloping land conversion program on household production efficiency under spatial heterogeneity and output diversification. *China Agricultural Economic Review*, *7*(2), pp.221-239.

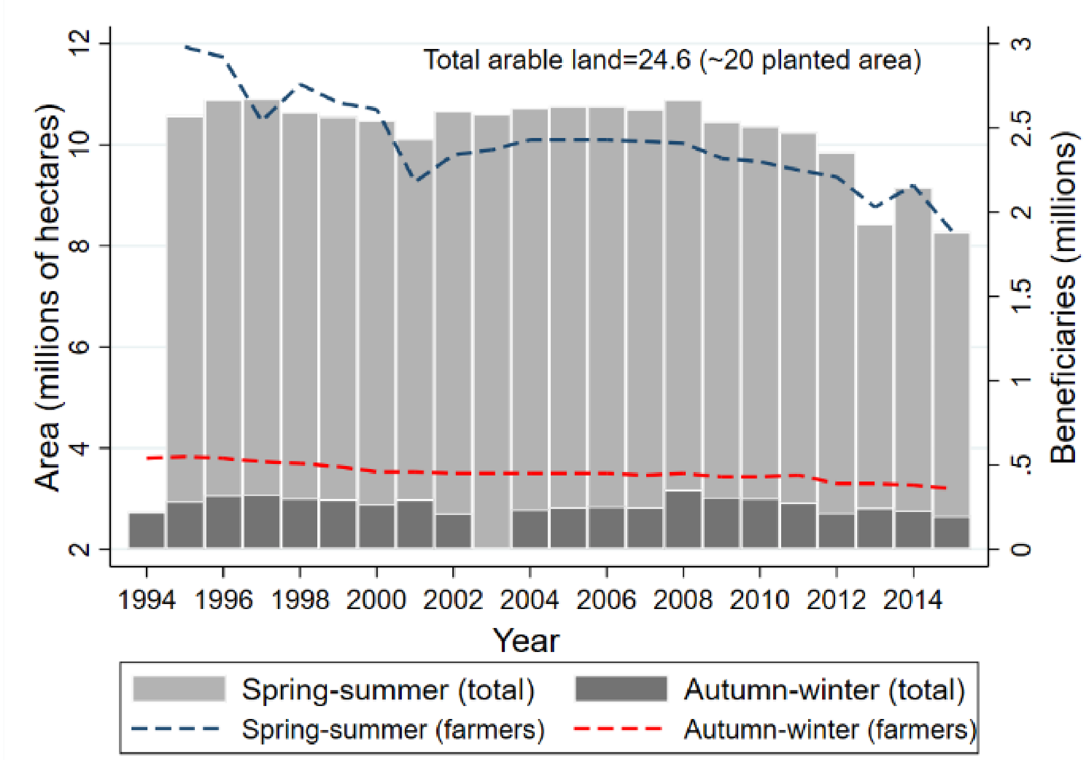
Zhu, X. and Lansink, A.O., 2010. Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *Journal of Agricultural Economics*, *61*(3), pp.545-564.

Zhu, X., Karagiannis, G. and Oude Lansink, A., 2011. The Impact of Direct Income Transfers of CAP on Greek Olive Farms' Performance: Using a Non-Monotonic Inefficiency Effects Model. *Journal of Agricultural Economics*, *62*(3), pp.630-638.

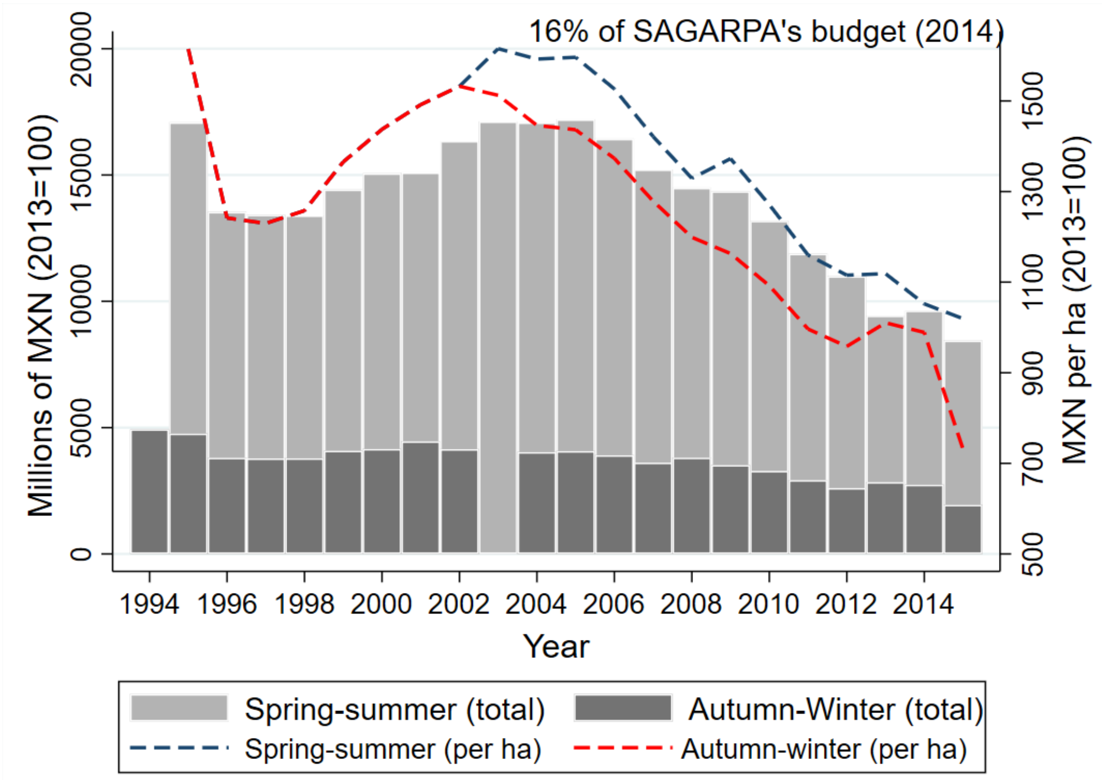
# Appendix

## *A4.1. Additional statistics*

**Figure 4.6 Distribution of PROCAMPO**




**4a. Subsidised area and beneficiaries**




**4b. Total cash transfer**

Source: own elaboration based on INEGI (2014) and SAGARPA (2017)

### *A4.2. Data Envelopment Analysis and Stochastic Frontier models*

**Table 4.8 CCR Data Envelopment Analysis models**

| **Input-oriented** | |
|---|---|
| **Envelopment model** | **Multiplier model** |
| $\min \theta - \varepsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$ | $\max z = \sum_{r=1}^{s} \mu_r y_{ro}$ |
| subject to | subject to |
| $\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad i = 1, \dots, m;$ | $\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$ |
| $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r = 1, \dots, s;$ | $\sum_{i=1}^{m} v_i x_{io} = 1$ |
| $\lambda_j \geq 0 \quad j = 1, \dots, n;$ | $\mu_r, v_i \geq \varepsilon > 0$ |
| **Output-oriented** | |
| **Envelopment model** | **Multiplier model** |
| $\max \varphi + \varepsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$ | $\min q = \sum_{i=1}^{m} v_i x_{io}$ |
| subject to | subject to |
| $\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \quad i = 1, \dots, m;$ | $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0$ |
| $\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{ro} \quad r = 1, \dots, s;$ | $\sum_{r=1}^{s} \mu_r y_{ro} = 1$ |
| $\lambda_j \geq 0 \quad j = 1, \dots, n;$ | $\mu_r, v_i \geq \varepsilon > 0$ |

$\theta$: efficiency score (ratio)
$\varphi$: efficiency score (ratio)
$\varepsilon$: non-Archimedean element smaller than any positive real number
$m$: total number of $i$-th inputs
$s$: total number of $r$-th outputs
$n$: total number of $j$-th farms to be evaluated
$s_i^-$ , $s_r^+$ : slack variables to transform inequalities into equalities
$x_{ij}$: amount of input $i$ used by farm $j$
$x_{io}$: observed input value of the farm to be evaluated
$y_{rj}$: level of output $r$ produced by farm $j$
$y_{ro}$: observed output value of the farm to be evaluated
$\lambda_j$: set of parameters
$z$: efficiency score (ratio)
$q$: efficiency score (ratio)
$\mu_r$: returns to scale parameter (multipliers)
$v_i$: returns to scale parameter (multipliers)

Source: adapted from Cooper et al. (2011)

**Table 4.9 An overview of the SFA models**

| Input-oriented | Output-oriented |
|---|---|
| $y = f(\boldsymbol{x} * \exp(-\eta)), \quad \eta \geq 0$ <br> or <br> $y = f(x * e^{-\eta})$ <br> where for small values of $\eta$: <br> $\text{TE} = \exp(-\eta) = 1 - \eta = 1 - TI$ | $y = f(\boldsymbol{x}) * \exp(-u), \quad u \geq 0$ <br> or <br> $y = f(x) * e^{-u}$ <br> where for small values of $u$: <br> $TE = \exp(-u) = 1 - u = 1 - TI$ |

**Functional forms of production functions**

**Cobb-Douglas production function (Cobb and Douglas (1928))**

$$\ln y = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_j$$

**Generalised production function (Zellner and Revankar (1969))**

$$\ln y + \theta y = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_j$$

**Transcendental production function (Halter (1957))**

$$\ln y = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_j + \sum_{j=1}^{J} \alpha_j \,.\, x_j.$$

**Translog production function (Christensen et al. (1973))**

$$\ln y = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{K} \beta_{jk} \ln x_j \ln x_k, \qquad \beta_{jk} = \beta_{kj}$$

$y$: level of output
$f(.)$: production function (frontier)
$\boldsymbol{x}$:non-negative input vector
$\eta$: measurement of input-oriented technical inefficiency
$u$: measurement of output-oriented technical inefficiency
TE: technical efficiency scores
$TI$: technical inefficiency
$J$ or $K$: total number of inputs

Source: adapted from Kumbhakar et al. (2015)

## *A4.3. Control variables in the existing literature*

**Table 4.10 Set of variables in the existing literature (Frontier function)**

| Variable | Description | Units |
|---|---|---|
| | ***Stochastic Production Function*** | |
| $y_i$ | Total value of output deflated by the corresponding price index (or quantities) | $, litres, kg |
| $land_i$ | Total utilised agricultural land | ha |
| $labour_i$ | Total labour including hired and family workers | hours, $ |
| $capital_i$ | Total value of stock of capital or total depreciation value (machinery, buildings, equipment, breeding herd, etc.) or total horsepower of agricultural machinery and total electric motors | $, HP |
| $inputs_i$ | Other expenses on purchased inputs (intermediate expenses) or quantities e.g. fertilisers, or disaggregated expenses on fertilisers, seeds, crop protection, feed, veterinary fees, energy, etc. | $, kg/ha |
| | ***Stochastic Production Function (other variables)*** | |
| $ext_i$ | Use of extension services (public and private) | visits |
| $arid_i$ | Aridity index, ratio of annual temperature to total volume of rainfall | ºC/mm |
| $alt_i$ | Altitude | masl |
| $soil_i$ | Soil quality (dummy variables) | dummy |
| $change_i$ | Dummy variables for policy reforms | dummy |
| $lfa_i$ | LFA payments (dummy variables) | dummy |

**Table 4.11 Set of variables in the existing literature (Technical inefficiency function)**

| Variable | Description | Units |
|---|---|---|
| | ***Farmers' characteristics*** | |
| $edu_i$ | Farmer's years of education | years |
| $age_i$ | Age of the farmer or farm's manager | years |
| $exper_i$ | Number of years as a farmer | years |
| | ***Farm characteristics (managerial practices and physical characteristics)*** | |
| $rented_i$ | Ratio of rented/owned land to total agricultural land | % |
| $hire_i$ | Ratio of hired/family labour to total labour or dummy variable for farm hiring labour | %, dummy |
| $debt_i$ | Ratio of total debt to total assets (cows) or total debt | %, $ |
| $spec_i$ | Specialisation, share of the main output in total output, or the Herfindahl index, or multiple cropping index | % |
| $exter_i$ | Share of output sold in the external market | % |
| $market_i$ | Share of marketed output in total output (or self-consumption) | % |
| $offinc_i$ | Off-farm income or off-farm job | $, dummy |
| $ltol_i$ | Land to labour or capital to labour ratio | ha-$/worker |
| $sub_i$ | Share of total, coupled, or decoupled subsidies in total farm income; or total value of subsidies (per unit of land); or dummy variables indicating whether a farmer receives a subsidy or not | $, $/ha, dummy |
| $ext_i$ | Use of extension services or participation in management workshops (years) | dummy, years |
| $insem_i$ | Use of artificial insemination | dummy |
| $syst_i$ | Different production/farming systems (dummy variables) | dummy |
| $treat_i$ | Cows under bovine somatotropin treatment | % |
| $stall_i$ | Use of free stall housing | dummy |

| | | |
|---|---|---|
| $feed_i$ | Ratio of purchased feedstuffs to the number of cows | % |
| $save_i$ | Family savings | $ |
| $inves_i$ | Investment per cow or total investment | $ |
| $inten_i$ | Intensive farming operations or hectares per livestock unit | dummy, ha/units |
| $seed_i$ | Type of seeds (modern variety or not) | dummy |
| $crop_i$ | Share of cropped land | % |
| $insur_i$ | Share of crop insurance income to total farm income as proxy to weather conditions (or disaster payments) | %, $ |
| $inputs_i$ | Expenses of different inputs per acre (seed, fertiliser, pesticides, veterinary fees, and machinery) | $/acre |
| $plan_i$ | Improvement plan is carried out in the farm | dummy |
| $pes_i$ | Farm environmental payments as a proportion of total income or total amount of environmental payments | %, $ |
| $enter_i$ | Entrepreneurial orientation index | index |
| $organ_i$ | Organic farms | dummy, % |
| $legal_i$ | Legal status of the farm | dummy |
| $mec_i$ | Number of hours of mechanical operations | hours |
| $mobile_i$ | Number of telephones per 100 people | units |
| $manage_i$ | Workers per manager | persons |
| $size_i$ | Farm or herd size (farmland or number of animals) | ESU |
| $irriga_i$ | Type of irrigation (water pump or not) or irrigation (irrigated or not) or share of irrigated land | dummy, % |
| | ***External factors*** | |
| $price_i$ | Price of the relevant output | $/litre,$/kg |
| $region_i$ | Regional dummies | dummy |
| $water_i$ | Dummy variables for water rights regimes | dummy |
| $road_i$ | Road density in the corresponding region | km/km2 |
| $soil_i$ | Index of soil quality | %,EMZ/ha |
| $lfa_i$ | Less Favoured Areas (dummy variables) | dummy |
| $alt_i$ | Altitude (proxy of geoclimatic heterogeneities) | dummy |
| $quota_i$ | Milk quota | kg/year |
| $tax_i$ | Simplified sales tax | dummy |
| $vote_i$ | Green voters | persons |
| $dist_i$ | Distance to the next dairy | km |
| $change_i$ | Dummy variables for structural changes such as EU accession, policy reforms, etc. | dummy |
| $env_i$ | Environmental restrictions | dummy |

### *A4.4. Variables description*

*Dependent variable:*

a) Total output:

$$y_i = \sum_{n=1}^{N} y_{n,i}$$

Where, $y_i$ is the total output per farm and $n$ are annual crops in the sample. It includes the value of annual crops produced in the 2014 agricultural year.[183]

*Frontier variables:*

a) Total ownership cost of capital ($TOC_i$):

$$TOC_i = \sum_{l=1}^{L}(CR_{il} + TIH_{il})$$

$$CR_{il} = (D_{il} * CRF_{li}) + (SV_{il} * r)$$

$$D_{il} = PP_{il} - SV_{il}$$

$$SV_{il} = PP_{il} - RVF_{il}$$

$$TIH_{il} = 0.01 * (PP_{il} + SV_{il})/2$$

$CR_{il}$ is the capital recovery cost of the $l$-th equipment or machine, $TIH_{il}$ are taxes, insurance and housing costs, $D_{il}$ is total depreciation, $CRF_{li}$ is the capital recovery factor in Edwards (2011), $SV_{il}$ the salvage value, $r$ is the real interest rate,[184] $PP_{il}$ is the current list price[185] and $RVF_{il}$ is the remaining value factor in Edwards (2011).

b) Total area: is the total utilised area in the production of the corresponding output

c) Working hours:

[183] Barley, maize, oat, rice, sorghum, wheat, beans, chillies, cotton, potatoes, soy, green tomato, melon, onion, red tomato, squash, and watermelon.

[184] We use an interest rate of 3.25%, which is the 1995-2014 average in Mexico.

[185] We use prices of machinery and equipment released by the Secretariat of Agricultural, Livestock, Rural Development, Food and Fishery of Mexico (SAGARPA). The list is available on: http://www.sagarpa.gob.mx/agricultura/Precios/Paginas/PreciosdeMaquinariaAgricola.aspx

$$working\ hours_i = wh_{hg6,i} + wh_{hl6,i} + wh_{jor,i} + wh_{fam,i}$$

where, $wh_{hg6}$, $wh_{hl6}$, $wh_{jor}$, and $wh_{fam}$ are the total number of working hours spend on farming activities from workers hired for 6 months or more, workers hired for less than six months, 'jornaleros', and family members respectively.[186]

d) Intermediate inputs

$$intermediate\ inputs = \sum_{l=1}^{L} expenses_l$$

where, $expenses_l$ are annual expenses and $l =$ {preparation of land/substrate, sowing/planting, fertilisers, plagues control, harvesting activities, balanced feed, medicines, vaccines, surgeries, veterinary fees, rent payments (machinery, equipment, and facilities), technical support (extension services), gasoline, diesel, oils, additives, electricity, freight charges, irrigation rights, taxes, interests, other expenses, output for self-consumption (seeds and livestock feed)}.

*Technical inefficiency variables:*

a) Age of the farmer

b) Schooling (years of study)

c) Area-owned

$$owned_i = (owned_i / total\ area_i) * 100$$

d) Hired labour

$$hired\ labour_i = \left((wh_{hg6,i} + wh_{hl6,i} + wh_{jor,i}) / working\ hours_i\right) * 100$$

e) Specialisation: Herfindahl index

[186] There were 253 working days from 1 October 2013 to 30 September 2014. Assuming a working day of 8 hours, the total number of working hours per annum is 2,024. Thus, $wh_{hg6,i}$ is the number of workers hired for or more than 6 months times 2,024. $wh_{hl6,i}$ is the number of workers hired for less than 6 months times 1,012. $wh_{jor,i}$ is the number of 'jornaleros' times the average number of working hours per day and 'jornal' times the total number of working days of the corresponding 'jornalero'. Moreover, $wh_{fam,i}$ is the sum over family members of the average number of hours that each member spends on farming activities per day times 253.

$$HI_i = \sum_{j=1}^{J} \left(A_{ji}/TA_i\right)^2$$

f) Irrigated area

$$irrigated\ area_i = (irrigated\ area_i/total\ area_i) * 100$$

g) Abroad (dummy variable for farms selling abroad directly)

h) PROCAMPO (dummy variable)

$$Procampo_i = \begin{cases} 1 & receives\ Procampo \\ 0 & otherwise \end{cases}$$

**Table 4.12 Model specification tests**

| Hypothesis 1 | | | LR-Test | d.f. | Prob>$\chi^2$ |
|---|---|---|---|---|---|
| Model (1) nested in model (2) | H1: $\gamma_0 = 0$ and $\gamma_m = 0$ | $\forall\ m$ | 2,414*** | 9 | 0.00 |
| Model (1) nested in model (3) | H1: $\gamma_0 = 0$ and $\gamma_m = 0$ | $\forall\ m$ | 2,537*** | 17 | 0.00 |
| Model (4) nested in model (5) | H1: $\gamma_0 = 0$ and $\gamma_m = 0$ | $\forall\ m$ | 2,007*** | 9 | 0.00 |
| Model (5) nested in model (6) | H1: $\gamma_0 = 0$ and $\gamma_m = 0$ | $\forall\ m$ | 2,095*** | 17 | 0.00 |
| **Hypothesis 2** | | | | | |
| Model (2) nested in model (3) | H1: $\vartheta_0 = 0$ and $\vartheta_m = 0$ | $\forall\ m$ | 123*** | 8 | 0.00 |
| Model (5) nested in model (6) | H1: $\vartheta_0 = 0$ and $\vartheta_m = 0$ | $\forall\ m$ | 88*** | 8 | 0.00 |

# Chapter 5 Conclusions, limitations and further research

The Intergovernmental Panel on Climate Change (IPCC) states that the concentration of greenhouse gases in the atmosphere will continue to increase in the years to come (IPCC, 2014). High concentrations of such gases rise the probability of trapping heat in the lower atmosphere. This additional heat would likely warm the sea and land surface temperature. Held and Soden (2006) states that global warming influences the hydrological cycle, and consequently, evaporation rates and rainfall patterns. Such changes would likely pose important challenges to humans such as health issues, higher frequency of extreme events, coastal and river floods, changes in coral reef systems, higher frequency of wildfires, losses of food production, and food quality.

Agriculture has been widely recognised as one of the most vulnerable sectors since agriculture yields highly depends on climate. In order to understand how climate change would affect the agriculture sector, this thesis comprises three interrelated essays that look at the effects of climate change on agriculture. In the first essay, we analyse the capitalisation of climate change in net revenues and rental prices, which hypothetically represent agricultural land rents. To assess the effect of climate change on land rents, we combine farm-level information on 76,094 farms[187] in Mexico with very high-resolution climate data (~1km$^2$ resolution Geographic Information System (GIS)-database) released by Hijmans et al. (2005) and estimate a set of Ricardian Hedonic models for the 2012 and 2014 agricultural years.

By investigating this phenomenon, the contributions of this essay to the existing literature are twofold. Unlike Mendelsohn et al. (2010) and Galindo et al. (2015), who estimate a Ricardian Hedonic model using a non-representative number of farms and municipal-level data from Mexico respectively, we obtain implicit prices of temperature and rainfall and speculate about

[187] 17,351 and 58,743 farms in the NAS-2012 and NAS-2014 surveys respectively.

the capitalisation of climate change on land rents using a farm-level country-representative sample. The National Agriculture Survey (NAS) collects data on rental prices and net revenues for the same farmsteads. This allows us to estimate a Ricardian Hedonic equation for a subsample of farms for which we observe both net revenues and rental prices. By doing so, we examine the appropriateness of measuring land rents through annual net revenues in the Ricardian Hedonic model, which we believe are more sensitive to annual whether than rental prices and are more likely to suffer from measurement errors.

Due to farmers' adaptation behaviour remains as a 'black box' in the Ricardian Hedonic model, in the second essay, we investigate how farmers would likely switch crops and/or types of livestock as a response to changes in climate. Rather than using farm-level data, we analyse agriculturalists' observed choices among 31 agriculture commodities encountered in 388,250 plots[188] corresponding to the 2012 and 2014 agricultural years. To identify the relationship between climate and farmers' choices, we use GIS tools to combine data on observed choices with climate information in Hijmans et al. (2005) and estimate two discrete choice models: Multinomial Logit and Nested Logit models.

Previous studies looking at the effect of climate on farmers' choices assume that such decisions are independent of the existence or the absence of other alternatives, that is, the Independence of Irrelevant Alternatives property holds. This seems to be unrealistic because if climate changes, it may force farmers to move their production efforts to the production of other agriculture commodities, which are more suitable for the new climate and are not necessarily in the choice set. For instance, the production of sheep may become suitable for a drier and warmer future. If there are some farmers currently harvesting beans and alfalfa, the inclusion of sheep in the set of alternatives will likely modify the odd-ratio[189] between beans and alfalfa

[188] 219,985 and 168,265 plots in the NAS-2012 and NAS-2014 surveys respectively.
[189] Probability of choosing beans over the probability of choosing alfalfa.

in favour of the latter, since alfalfa is an input in the production of sheep. By estimating a Nested Logit (NL) model, we relax the Independence of Irrelevant Alternatives (IIA) assumption, group together similar alternatives (or alternatives that can be jointly produced) and estimate dissimilarity parameters that measure the degree of correlation among farmers' observed choices.

Unlike the existing literature, we simultaneously examine transitions between arable and non-arable activities rather than analysing transitions within such activities separately. The spatial distribution of farms permits the inclusion of the full set of expected farm-gate output prices in the choice equations rather than ex-post values, which might not be relevant because farmers make the corresponding decisions at the beginning of the agricultural year. Aside from using expected prices, we seek to improve previous estimations by setting cross-prices to zero in the choice equations since such prices are not arguments of the profit function.

Apart from switching crops and/or types of livestock, farmers should use available inputs more efficiently to offset harmful effects of climate change on agriculture. In the third essay, we use the parametric stochastic frontier model to compute technical efficiency scores and assess the current performance of 33,721 Mexican farms that harvest annual crops. Furthermore, we investigate the association between agricultural subsidy payments and farms' technical efficiency to test whether subsidy payments prevent farmers to use available inputs more efficiently or not.

At the same time that we assess the performance of Mexican farms, for which there are no prior assessments, we also contribute to the existing debate about the influence of subsidy payments on farms' technical efficiency by providing additional empirical evidence from a developing country. In contrast to previous investigations, which in the best case estimate decile-specific parameter estimates, we use Recentered Influence Function regressions and the Wang's (2002) formula to compute percentile-specific and farm-specific marginal effects of the subsidy-technical efficiency association respectively. These estimations allow us to identify differential associations within the sample.

The main findings of this thesis suggest that one additional degree Celsius, with respect to current temperature, would change rental prices and net revenues by approximately -16%-(+)18% and -113%-(+)109% respectively (-18%-(+) 21% and -270%-(+)280% in farms with 100% rented land respectively). Regarding rainfall, one additional mm. of rain would likely change current rental prices and net revenues by approximately -0.16%-(+)0.08% and -0.26%-(+)0.71% respectively (-0.44%-(+) 0.13% and -0.47%-(+)0.53% in farms with 100% rented land respectively). The divergences between implicit prices of climate resulting from both Ricardian Hedonic models arise either because there is much more variation in net revenues than in rental prices, some farms are so inefficient that the costs of inputs offset land rents, or there exist measurement errors in the net revenues variable.

The abovementioned finding has important implications for existing and future investigations using net revenues to approximate land rents. We face several difficulties to compute net revenues at the farm-level such as measuring the annual cost of both human-made and biological (natural) capital, which is also an issue in previous studies (Eid et al., 2007; Molua and Lambi, 2007; Jain, 2007; Deressa, 2007; Mano and Nhemachena, 2007). To deal with this issue, we use all available information about human-made capital to compute the total ownership cost of each machine and equipment in the corresponding farm. However, measuring the cost of biological (natural) capital is not straightforward. In this context, the annual cost of capital is likely to be below its actual value. Therefore, those farms that extensively use different means of biological (natural) capital, such as oxen, tend to report higher net revenues. This is very likely to happen in developing countries where most of previous investigations use net revenues to speculate about the effect of climate change on agriculture.

Aside from the difficulties to compute annual net revenues, we observe some farms for which non-land costs exceed revenues, that is to say, these farms operate with negative net revenues. In developing countries, one usually observe a relatively large number of inefficient farms[190] with negative net revenues, which remain in the market thanks to subsidisation programmes, e.g. to promote food security or to alleviate poverty in rural areas. Darwin (1999) argues that the presence of negative values contradicts the economic principle of non-negative land rents. This issue has not been fully addressed in the existing literature. To deal with negative values in the Ricardian Hedonic model, we use the *neglog* transformation proposed by Whittaker et al., (2005). Although this transformation allows using the entire sample in the hedonic model, it is still difficult to justify negative values of land rents, which does not happen when researchers use rental prices or land values instead. The strand of literature using net revenues argues that land values are rarely available in developing countries. However, this thesis aims to rise a question about how much we gained by using flawed measures of land rents, especially when we look at the effects of climate change on agriculture.

We also find that climate indeed influences farmers' crop and livestock choices. In contrast to the existing literature, we encounter that such choices depends on the existence or the exclusion of other alternatives. The set of Hausman tests shows that removing alternatives one by one from the full set of available options (31 alternatives) in the Multinomial Logit (MNL) model clearly modifies odd-ratios of the remaining alternatives. Thus, we find strong evidence about the inappropriateness of the IIA assumption. To understand the correlation of choosing similar commodities or commodities that can be jointly produced, we estimate a NL model and the corresponding dissimilarity parameters. The results show that farmers choose agricultural commodities classified as cereals, fruits, and other crops[191] with high correlation and different types of livestock with moderate-low correlation. After accounting for correlation patterns,

[190] We encounter empirical evidence about this argument in the next chapter and also in the existing literature.
[191] Alfalfa, beans, chilies, cotton, potato, soy and sugar cane.

speculations about the effect of climate change on farmers' choices suggest that Mexican agriculturalists would move their production efforts from alfalfa, beans, cacao, beef cattle, red tomato, and sugar cane to the production of barley, pigs, and potato.

The existence of correlation patterns among farmers' choices in Mexico cast some doubts on the conclusions drawn from previous investigations. Treating farmers' choices as if they were independent of the existence of other alternatives may lead to flawed conclusions because it is likely that new crops or new types of livestock will become more suitable for future climate. If so, the inclusion of such new alternatives in the choice set would likely modify the odd-ratios between any pair of existing alternatives. The correlation of choosing alternatives within the same subset of commodities, e.g. cereals in the NL model, arises because these crops share some similarities such as their suitability to grow under certain climate conditions or use similar types of capital. It is highly probable that climate change forces farmers to choose different crops or types of livestock, and consequently, different equipment and machinery. Unlike previous studies using the MNL model, future investigations about the effects of climate change on crop and livestock choices should consider correlation patterns since farmers would firstly look at those alternatives that are closely similar to the current choices rather that looking at options that can only be produced with drastic changes in capital.

In recent years, Seo and Mendelsohn (2008) and Chatzopoulos and Lippert (2015) seek to explicitly model farmers' adaptation behaviour in the Ricardian Hedonic approach through crop and livestock choices. This approach is known as the 'structural Ricardian model', which uses the MNL to model farmers' choices in a first stage, then introduce the selection terms in the traditional Ricardian Hedonic model in the second stage and speculate about potential effects of climate change on agriculture. The results of this thesis have also implications for the structural approach. The use of a NL model in the first stage of the structural Ricardian model instead of the MNL model would allow future research to relax the IIA property and improve future assessments.

The assessment of farms' performance also provides us with interesting findings. Overall, we find that Mexican farms are in average highly inefficient. The average technical efficiency of farms in the sample is of 46%, that is, these farms can produce almost twice the output they are currently producing using the same inputs. Furthermore, we find that subsidies (*'Programa de Apoyos Directos al Campo'* (PROCAMPO)) negatively influences farms' technical efficiency in 74% of the farms. Such negative association increases as technical inefficiency rises. In other words, subsidies have larger negative impacts on those farms that are already inefficient than on farms that operate closer to the maximum attainable output (frontier). Interestingly, the age of the farmer, years of schooling, the percentage of area-owned, the use of hired-labour, diversification of agriculture activities, and the use of irrigation increase technical efficiency.

The existence of large technical inefficiencies in the agriculture sector in Mexico represents an opportunity for farmers to use available inputs more efficiently and partially or wholly offset harmful effects of climate change. According to IPCC (2014), developing countries, where the existing literature found highly inefficient farm, are more vulnerable to climate change than other countries. Under such circumstances, policy-makers should promote policies aiming to increase farms' technical efficiency. In this regard, the main results of this thesis suggest that policy-makers can enhance technical efficiency by providing farmers with extension services (or education), giving more incentives to farmers to increase the proportion of hired labour in the farm, and contribute to the installation of irrigation systems.

Subsidy payments negatively influence technical efficiency of most of the farms in Mexico. Such finding corroborates the empirical findings in the existing literature, especially in Europe (Minviel and Latruffe, 2017). The immediate implication of such result is that policy-makers should get rid of the subsidy (PROCAMPO) if technical efficiency were the main target.

However, some studies show that PROCAMPO creates a multiplier income-effect in the *ejidal* sector (Sadoulet et al., 2001), reduces rural migration from Mexico to the United States of America (USA), and increases the use of labour in the production of corn and beans, which are the staple foods in several regions (Gonzalez-Konig and Wodon, 2005; Scott-Andretta and Cuecuecha, 2010). Therefore, policy-makers should adjust the eligibility criteria in order to consider farms' technical efficiency. For instance, the recipient should spend a portion of the subsidy payment on extension services where possible.

To interpret the main findings of this research, the reader should be aware of the following caveats. First, aside from the difficulties to compute annual net revenues, such as calculating the cost of biological (natural) capital, we do not observe the length of rental agreements. Therefore, rental prices in the Ricardian Hedonic models might not reflect land rents in those cases in which the rental price was agreed some years prior to the 2012 and 2014 agricultural years. Second, the lack of panel data prevents us to consider crop rotation practices in the set of choice equations. Moreover, farmers' risk attitudes are not fully accounted for in the discrete choice models. Although we construct a farm-specific Herfindahl index to measure the degree of diversification, the small variation of this index within the sample prevents some models to converge, and consequently, to examine farmers' risk attitudes via diversification of agriculture activities. This happens because there are several full-specialised farms in the sample, especially those harvesting maize. Third, the lack of panel data also prevents us to examine technological progress in the stochastic frontier functions. Furthermore, we also acknowledge that the stochastic frontier model may suffer from sample selection bias since the initial allocation of PROCAMPO in 1994 is not part of the estimation. Fourth, the speculations about the effects of climate change on agriculture solely assume changes in long-term climate and that other factors remain unchanged. Therefore, the reader should be aware of that these predictions would be different if technological progress occurs, the demand for food rises, the availability of water changes, new crops or types of livestock enter in the choice set, new lands are put into cultivation, and the production of genetically modified crops and/or types of livestock is permitted in Mexico in the years to come.

To further contributing to the existing literature, future studies should consider the following steps. Researchers using annual net revenues in the Ricardian Hedonic regression should test whether such measures are sensitive to climate or not by replacing long-term averages with annual weather or deviations from the long-term climate. The fact that we observe net revenues at the end of the agricultural cycle makes this measure highly sensitive to annual weather rather than to the observed climate in the last decades. For example, unusual heavy rain may largely harm crops but that does not imply that such a land is infertile in normal conditions. Under such circumstances, the inclusion of annual weather or deviations from their normal values allows future studies to test for such sensitiveness and provide better estimates. Given the nature of climate data in Hijmans et al. (2005), which only reports normal values, we were unable to use annual weather or deviations from the normal values using the same GIS-database. Although meteorological station data is available for Mexico, linking such data with our GIS-database requires an important amount of work, e.g. interpolating climate data at ~1 $km^2$ resolution. Therefore, we leave this for future research.

Future studies should also make an effort to include the cost of biological (natural) capital in the net revenues calculation. To compute the ideal measure of the cost of capital, one should account for the cost of using and non-using biological capital, manufactured capital, and financial capital. In this thesis, we were unable to account for every single component of the cost of capital. Unfortunately, the NAS does not collect data on the number of oxen, the frequency in which farmers use oxen, the associated cost to benefits from biodiversity, e.g. pollination, the cost of debt, and the cost of non-rented facilities. Thus, future studies should make an effort to properly computing the cost of capital, especially biological capital.

Regarding discrete choice models dealing with farmers' observed choices, future research should estimate a Multinomial Probit model (Alternative-Specific Multinomial Probit (ASMP)) to obtain a full correlation matrix rather than estimating an average correlation among similar alternatives through the NL model. From the research work in this thesis, we realise that correlation parameters in the NL model are somehow sensitive to the nest design. There exist several nest designs that could lead to different results, e.g. grouping together alternatives that use similar means of capital and therefore farmers produce them at the same time. Under such circumstances, one should estimate an ASMP model to obtain correlations among individual commodities. Given the complexity in the estimation of the ASMP model, the large number of alternatives in the choice set, and that there is not enough data on alternative-specific attributes, we were unable to estimate such a model.

Another area that deserves further research is the analysis about how subsidies (cash transfers) may stop farmers to switch from one crop to another in order to adapt to future climate. We encounter that farmers, who receive PROCAMPO and *'PROGAN productivo'* (PROGAN), tend to choose traditional commodities with higher probabilities, e.g. maize, beans, and beef cattle. This is likely to happen because farmers do not have enough incentives[192] to choose crops/livestock that are more suitable for a new climate because the subsidy payments can compensate the gains from choosing crops/livestock other than the current ones. Although we briefly analyse this issue, it deserves further investigation.

Regarding the stochastic frontier estimation, further analyses of the subsidy-technical efficiency link in Mexico should test for the presence of endogeneity and selection bias. The former issue may arise when farmers adjust intermediate inputs in the middle of the production cycle as a response to stochastic events such as weather socks or plagues, which are typically part of the error term. For the latter, one may argue that PROCAMPO was not randomly

[192] Avoiding damages from cultivating the same crop under an unsuitable climate.

allocated in 1994 and therefore, the stochastic frontier model suffer from sample selection bias. Although Greene (2010) and Latruffe et al. (2017) propose a normal-half normal stochastic frontier model and a four-step method to deal with endogeneity and sample selection issues in the stochastic frontier model respectively, we were unable to test for such issues in this thesis due to data and time restrictions. Therefore, future research should include such tests.

## References

Chatzopoulos, T. and Lippert, C., 2015. Adaptation and climate change impacts: A structural Ricardian analysis of farm types in Germany. *Journal of Agricultural Economics*, *66*(2), pp.537-554.

Darwin, R., 1999. The impact of global warming on agriculture: A Ricardian analysis: Comment. *American Economic Review*, *89*(4), pp.1049-1052.

Deressa, T.T., 2007. *Measuring the economic impact of climate change on Ethiopian agriculture: Ricardian approach*. The World Bank.

Eid, H.M., El-Marsafawy, S.M. and Ouda, S.A., 2007. Assessing the economic impacts of climate change on agriculture in Egypt: a Ricardian approach.

Galindo, L.M. and Reyes, O., 2015. Climate change, irrigation and agricultural activities in Mexico: A Ricardian analysis with panel data. *Journal of Development and Agricultural Economics*, *7*(7), pp.262-273.

González-Konig, G. and Wodon, Q., 2005. Do cash transfers to farmers reduce migration? Procampo in Mexico. *No. EC200501, Department of Economics and Finance Working Papers, Universidad de Guanajuato. http://econpapers. repec. org/paper/guawpaper/ec200501. htm*.

Greene, W., 2010. A stochastic frontier model with correction for sample selection. *Journal of productivity analysis*, *34*(1), pp.15-24.

Held, I.M. and Soden, B.J., 2006. Robust responses of the hydrological cycle to global warming. *Journal of climate*, *19*(21), pp.5686-5699.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. and Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology*, *25*(15), pp.1965-1978.

IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Jain, S., 2007. *An empirical economic assessment of impacts of climate change on agriculture in Zambia*. The World Bank.

Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y. and Moreira, V.H., 2017. Subsidies and technical efficiency in agriculture: Evidence from European dairy farms. *American Journal of Agricultural Economics*, *99*(3), pp.783-799.

Mano, R. and Nhemachena, C., 2007. *Assessment of the economic impacts of climate change on agriculture in Zimbabwe: A Ricardian approach*. The World Bank.

Mendelsohn, R., Arellano-Gonzalez, J. and Christensen, P., 2010. A Ricardian analysis of Mexican farms. *Environment and Development Economics*, *15*(2), pp.153-171.

Minviel, J.J. and Latruffe, L., 2017. Effect of public subsidies on farm technical efficiency: a meta-analysis of empirical results. *Applied Economics*, *49*(2), pp.213-226.

Molua, E.L. and Lambi, C.M., 2007. *The Economic Impact Of Climate Change On Agriculture In Cameroon, Volume 1of 1*. The World Bank.

Sadoulet, E., De Janvry, A. and Davis, B., 2001. Cash transfer programs with income multipliers: PROCAMPO in Mexico. *World development*, *29*(6), pp.1043-1056.

Scott-Andretta, J. and Cuecuecha, A., 2010. *The Effect of Agricultural Subsidies on Migration and Agricultural Employment* (No. DTE 474).

Seo, S.N. and Mendelsohn, R., 2008. Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management 1. *Agricultural economics*, *38*(2), pp.151-165.

Wang, H.J., 2002. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *Journal of Productivity Analysis*, *18*(3), pp.241-253.

Whittaker, J., Whitehead, C. and Somers, M., 2005. The neglog transformation and quantile regression for the analysis of a large credit scoring database. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *54*(5), pp.863-878.