ESSAYS ON THE ECONOMICS OF ENERGY IN CHINA

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Abstract

As a result of strong economic growth and an expanding population over the course of the last two decades, China has become one of the world's leading economies and the world's largest energy consumer. Given the importance of China to the world economy, and the essential role that energy plays, it is crucial to understand the energy-related economic challenges faced by China. This thesis investigates four related topics on the economics of energy in China. Topics include (1) the relationship between urbanization and energy efficiency, (2) the cost effect of energy on industrial structure, (3) gasoline price patterns, and (4) the impact of energy abundance on industrial production and trade distribution. The results emphasize the importance of urbanization and open-market policies in determining the energy usage in China, and suggest that energy prices and energy-related regulations are efficient instruments to promote resources reallocation across industries and resources relocation across regions.

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Chapter 1

Introduction

1.1 Energy and the Economy

In today's modern economy, energy is essential for economic activity and to maintain the current high quality of life found across the world. Looking forward, energy will continue to play a crucial role in driving future economic growth. Since the end of World War II, both the global economy and energy consumption have experienced dramatic growth especially during the last two decades. According to the U.S. Energy Information Administration (EIA), in 2016 the world's total primary energy consumption was double that of 1980. Over a similar period, the real gross world production has quadrupled from 18.8 trillion dollars in 1980 to 77.9 trillion dollars in 2014. Historically, nations that belong to the Organization for Economic Cooperation and Development (OECD) account for the majority of energy consumption. However, according to EIA's projections of the worldwide energy demand over the period from 2012 to 2040, much of the increase in energy consumption will come from the developing non-OECD counties. Figures 1.2 and 1.1 present the projections for the world's total gross domestic product (GDP) and energy consumption by regions respectively.

Fig. 1.1 World total gross domestic product (1990-2040, trillion 2010 dollars)

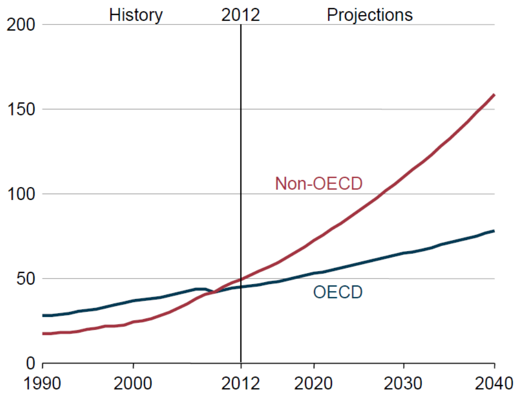
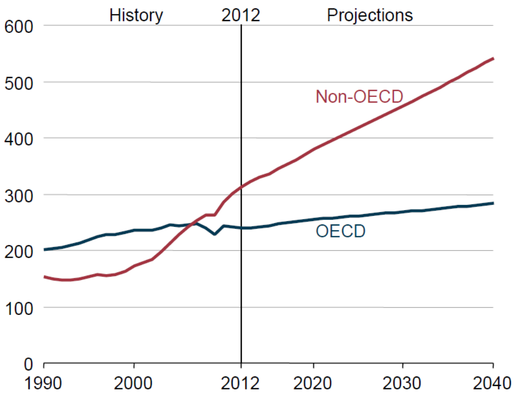


Fig. 1.2 World energy consumption (1990-2040 quadrillion Btu)



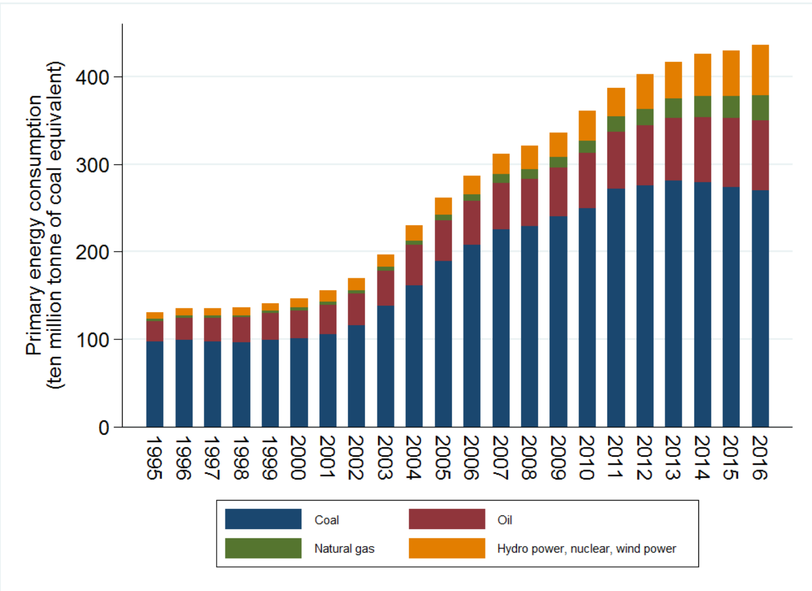
Source: U.S. Energy Information Administration, International Energy Outlook 2016

Accordingly, GDP in non-OECD countries surpassed the OECD total in 2010 and for energy consumption it was in 2007. By 2040 both of the GDP and energy demand in the non-OECD region are expected to exceed the OECD total by 80% to 100% respectively.

China, in particular, accounts for a significant part of the increase of worldwide energy demand. As a result of strong economic growth and an expanding population over the course of the last two decades, China has become one of the leading economies in the world. Despite the slowing down of economic growth, China is expected to have an annual average growth rate of 4.7% between 2012 to 2040. Over this period a transition is expected from being investment dominated to achieving a better balance between consumption and investment. China is also one of the world's leading trading nations, exported 2.06 trillion USD and imported 1.32 trillion USD in 2016, resulting in a positive trade balance of 736 billion USD. Its top trading partners include the US, Hong Kong, and Japan.

Meanwhile, China surpassed the US to become the world's largest energy consumer in 2010. Its primary energy consumption totaled 2,432 Mtoe (million tons of oil equivalent) with a recent annual growth rate of 11.2%. Figure 1.3 presents the composition of China's primary energy consumption from 1995-2016 and Figure 1.4 presents the trend in China's energy intensity during the same period. Figure 1.3 shows that China's primary energy consumption grew rapidly after 2000. Observe that although there has been an increase in energy supplied from renewable sources, coal and oil continue to supply the overwhelming majority of energy consumed. From 2003 coal consumption increased significantly leading to a rapid increase in overall energy consumption. This rise matches the period when both aggregate energy intensity and coal intensity in China reversed its previous decline and rose slightly in 2003 before resuming its gradual decline. According to the World Bank the energy intensity in China fell by 48% from 1995 to 2014, while for the same period the US experienced a decrease of 32%, the EU by 31%, and Japan by 23%.[1]

Fig. 1.3 Chinese national energy consumption composition (1995-2016)

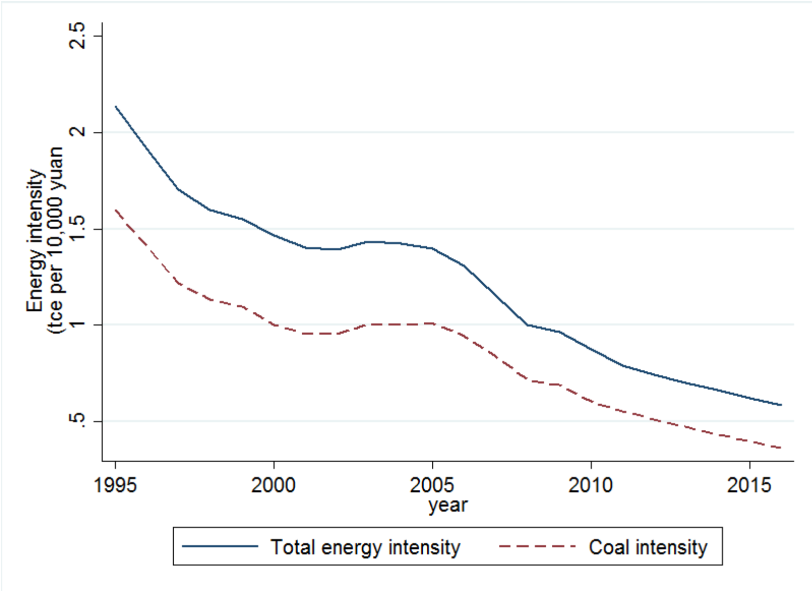


Source: National Bureau of Statistics of China, http://www.stats.gov.cn/

The increased energy demand raises several issues, and one of them is the energy security concern. The degree of China's dependence on energy imports increases continuously. The domestic demand-supply gap in 2014 reached 407 million tons of standard coal equivalent and the reliance on foreign crude oil reached a new record of 59.6% (People's Daily, 2014).

[1] Data source: http://data.worldbank.org/indicator/EG.USE.COMM.GD.PP.KD.

Fig. 1.4 Chinese aggregate energy intensity and coal intensity (1995-2016)



Source: National Bureau of Statistics of China, http://www.stats.gov.cn/

Environmental concerns in China have also been growing in recent years. Widespread problems of smog and haze have resulted in complaints and calls to reduce air pollution (The Economist, 2015).[2] The proliferation of serious environmental issues is related to the structure of China's energy resource reserves. China is relatively rich in coal reserves with total proven reserves totalling 114.5 billion tons at the end of year 2014 accounting for 12.8% of global reserves. In contrast, the proven reserves for oil and gas account for 1.1% and 1.8% of the global share respectively (British Petroleum, 2015). The endowment of natural resources makes it costly for China to develop alternative energy strategies.[3]

[2]http://www.economist.com/news/china/21661053-new-study-suggests-air-pollution-even-worse-thought-mapping-invisible-scourge

[3]According to Statistical Review of World Energy 2015 by British Petroleum, total proven reserves for oil, natural gas and coal in the US are 2.9%, 5.2% and 26.6% respectively.

1.2 Changing Structure of Power Sector and Energy Pricing

Given that energy consumption is one of the main causes of environmental issues in China, an energy-centric approach to the problem is needed. Reform of the power generation sector in China began in the 1980s. Previous interventions include replacing the centrally planned power generation system with a market-oriented system as well as approving energy related investments from local governments and domestic enterprises. The blueprint published in 2002 announced the divestment of the vertically integrated power utility, State Power Corporation, and the separation of power generation and transmission. China's current upstream industry consists of five large state-owned groups which account for more than 60% of power generation capacity. The transmission and distribution sector is comprised of two power grid corporations which cover the north and south of China respectively.[4]

In 2011, the government launched a progressive energy pricing reform plan following the 12th Five-Year Plan which promotes the market-oriented competition on energy markets. For historical reasons, China's energy prices are highly regulated and the prices often set for political reasons rather than being market driven. As an important political instrument, China uses energy prices to subsidize for the poor, and to encourage or restrict the development of specific industries depending on local governments' objectives. For example, cross-subsidies from industrial and commercial consumers to household consumers are prevalent even through household electricity consumption features a decentralized low voltage network with

[4]The State Power Corporation was founded in January 1997 and was dissolved in December 2002 with the aim of introducing more competition in the power sector in China. The five large gencos include China Huaneng Group, China Datang Corporation, China Guodian Corporation, China Huadian Corporation and China Power Investment Corporation. The two transmission and distribution corporations include State Grid Corporation of China and China Southern Power Grid Corporation. After the separation of generation from transmission, no single player should have more than a 20% share of capacity in an individual province. See Ngan (2010) for a comprehensive summary of the electricity market reform in China since year 1986.

large transmission losses and operational costs when compared to the electricity consumption of industrial and commercial consumers (Ecofys et al., 2015).

In terms of pricing energy, regional authorities appear to have substantial influence. In 2004 the preferential electricity price was required to be cancelled by the central government. It was used by provincial authorities to support energy intensive industries in their jurisdictions. Instead, the differential electricity price scheme was issued by the State Council. Firms operating in six energy-intensive sectors were classified into four categories: eliminated; restricted; permitted; and encouraged based on their products and manufacturing process.[5] A punitive surcharge was imposed on firms categorized as eliminated and restricted with an additional 0.05 yuan and 0.02 yuan per kWh imposed on consumed electricity. However, local authorities continued to evade the national policy for few year. Following the financial crisis 22 provinces maintained or reinstated the preferential electricity price for firms producing aluminum after the policy was first forbidden in 2004.[6] The scheme has been gradually terminated in most provinces after 2010.

1.3 Outline of the Thesis

Given the importance of China to the world economy, and the essential role that energy plays, it is crucial to understand the energy-related economic challenges faced by China. This thesis seeks to disentangle several interesting and up-to-date questions regarding energy usage and efficiency issues based on Chinese data. Starting from the aggregated level, the second chapter investigates the determinants of energy efficiency at the province level. I investigate

[5]The six energy intensive sectors include electrolytic aluminum, ferroalloy, calcium carbide, caustic soda, cement, iron and steel and the punitive surcharge is 0.05 yuan/kWh for the eliminated and 0.02 yuan/kWh for the restricted. In September 2006 two more sectors (phosphorus and zinc smelting) are added into the differential electricity price frame and the punitive surcharge was increased to 0.20 and 0.05 yuan/kWh respectively.

[6]See http://www.gov.cn/jrzg/2010-08/07/content_1672969.htm.

the impact of urbanization, income per capita and industrialization on the intensity of energy use in China using provincial panel data for the period 1995 to 2012. Two alternative measures of urbanization are employed taking into account China's "hukou" system, i.e. the household registration system that has lasted for more than 60 years and is directly related to the availability of social welfare. Utilizing a recently developed mean group estimation technique, I identify four impact channels through which urbanization affects energy usage in China.

The third and the fifth chapter look at the usage of energy at the micro level. I investigate how manufacturing firms react to increasing energy costs through product switching and geographic specializing. More specifically, in the third chapter I investigate how electricity prices affect firms' production choices during the period 2005 to 2007. Employing an instrumental approach to address potential endogeneity concerns, the results show that the energy price plays an important role in shifting industrial production towards less energy intensive industries.

In the fifth chapter of the thesis I investigate the impact of energy abundance on industry distribution and subsequent trade patterns in China. I utilize a cost-minimizing approach and estimate a pseudo-endowment indicator to proxy the provincial energy abundance level which is independent from regional industrial structure. Energy abundance is found to be an important determinant of industrial product shares at the 2-digit level. Furthermore, two mechanisms are explored underlying the impact of energy abundance, namely resource reserves and policy orientation. The findings from Chpater three and Chapter five shall help policy makers obtain a deeper understanding of firm behavioural mechanisms and develop effective policies to address energy and environmental issues.

Last but not least, the fourth chapter is inspired by China's open market policy and investigates the price effect of Royal Dutch Shell's entry into Chinese gasoline market. Using the difference-in-difference method on pair-wise absolute price differentials, our results suggest that Royal Dutch Shell's entry causes a price divergence in a certain period of time. Finally, the thesis concludes with a brief discussion of the main findings, policy implications and the limitations of the thesis. The thesis ends with an outline of future potential research topics related to energy economics in China.

Chapter 2

The Direct and Indirect Effect of Urbanization on Energy Intensity: A Province-level Study for China

Statement of Authorship

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Contribution to the Paper	Collected and cleaned the data, performed the econometric and statistical analysis and prepared the manuscript		
Overall percentage (%)	85%		
Signature	Tong Zhu	Date	08/09/2017

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Robert Elliott		
Contribution to the Paper	Supervised the development of the work and helped with the evaluation of the manuscript		
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Contribution to the Paper	Helped with data collection and manuscript evaluation		
Overall percentage (%)	5%		
Signature	Sun	Date	08/09/2017

The Direct and Indirect Effect of Urbanization on Energy Intensity: A Province-level Study for China

Abstract

In March 2014 China announced its long awaited plan for managing the migration of the rural population into already overcrowded urban areas. The so called "new style" of urbanization has potentially important implications for China's energy use. However, the relationship between urbanization and energy intensity is not straightforward. In this paper we investigate the impact of urbanization, income per capita and industrialization on the intensity of energy use in China using a balanced panel of 30 provinces for the period 1995 to 2012. Our empirical approach is to use two alternative measures of urbanization and employ augmented mean group (AMG) estimators to allow for heterogeneity in the estimation of the slope coefficients and cross sectional dependence. We demonstrate that the direct impact of urbanization on energy intensity is generally positive while the indirect impact through four different channels (construction, industrial upgrading, transportation and changing lifestyles) tends to be negative. On average, a one percentage point increase in urbanization in China leads to an increase in energy intensity of between 0.753 and 1.473 percent for electricity and coal intensity respectively although our results are sensitive to the measure of urbanization. Our results emphasize the importance of province heterogeneity in China which implies that national targets should be implemented with care.

JEL: Q43; R11; O14

Keywords: Energy intensity; Income per capita; Industrialization; Urbanization

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2.1 Introduction

The ability of both developed and developing countries to reduce the intensity of energy use is thought to play an important role in determining the world's capacity to grow sustainably in the future. Reducing the energy intensity of firms and households is considered to be a practical solution to many of today's common challenges including global energy shortages; mitigating against further changes in the climate; and reducing the impact on health of local air and water pollution. Understanding the factors that influence energy intensity are of first-order importance for academics and policymakers especially given the rise of rapidly growing and energy hungry economies such as China and India.[1]

The purpose of this paper is to investigate the determinants of province level energy intensity in China. Specifically, we examine the impact of urbanization, income per capita, and industrialization on energy intensity in China for a sample of 30 provinces for the years 1995 to 2012. In addition to examining the direct impact of these variables on energy intensity this research also examines a number of indirect channels (construction, transportation, industrial upgrading, and changing lifestyles) by which changing urbanization may effect energy intensity. This is a period in China's history categorized by rapid economic development and a correspondingly large increase in the demand for energy. From the 1990s to the current day China has experienced a steady but slow decline in energy intensity albeit with a period of rising energy intensity in the middle of the last decade. Hence, understanding the factors that drive changes in energy intensity in China is important for policymakers who are looking to develop instruments to address China's energy security and pollution concerns.

[1]In this paper we use energy intensity and energy efficiency interchangeably. However, strictly speaking, energy intensity measured as (1) the primary energy supply divided by the output ratio (GJ/$) or (2) energy consumption of standard coal equivalent per GDP and is usually considered to be part of the wider definition of energy efficiency. Energy intensity is therefore an indicator of, rather than equivalent to, energy efficiency. Energy efficiency means using less energy to provide the same service while energy intensity is a precise unit of measurement.

One of the factors thought to be important in the evolution of energy intensity is the role of urbanization.[2] Over the previous 35 years China has witnessed urban population growth of more than 500 million people (The Economist, 2014). Currently, China has the world's largest urban population (758 million), followed by India (410 million) (United Nations, 2014). These two countries now account for 30 per cent of the world's urban population. In the third plenum of the 18th Central Committee of the Communist Party of China made public on October 15th 2013 it became apparent that China's model of urbanization was changing. The previous model of rapid but inefficient urbanization is to be replaced with greater priority given to services and a larger role for the free market. The hope is that the changes will result in high quality urbanization. The thinking is that by putting additional emphasis on technology and the efficient clustering of factors of production there will be improvements in the efficiency of industrialization and hence a more efficient use of energy.

In March 2014, the long awaited first official plan on urbanization, namely the National New-Style Urbanization Plan (2014-2020), was issued by the Central Committee and the State Council to provide guidelines for the reasonable flow of migrants into urban areas. According to the National Migrant Workers Monitoring Survey Report 2014 issued by National Bureau of Statistics of China (NBSC, 2015), the total number of migrant workers reached 273.95 million with a growth rate of 1.9% in 2014. With the emphasis on city ecological progress and urban quality, the plan acknowledged an unequal treatment of rural migrant workers (due to the hukou system of household registration) and promises to help 100 million of the 260

[2] Urbanization is defined as the increase in the proportion of a population living in urban areas, or the process by which a large number of people becomes permanently concentrated in relatively small areas, forming cities (United Nations, 1997). The criteria for what constitutes an urban settlement vary from country to country, based on characteristics such as administrative criteria, a minimum population threshold, and population density (United Nations, 2014). During our study period the measure of urban districts used by China's National Bureau of Statistics is associated with both administrative criteria and population density (Qin and Zhang, 2014). According to United Nations (2014), if China was to reach Western levels of urbanization it would need to increase the level of urbanization by more than 23 percentage points. The urbanization rate of China will reach 55.6% in 2015 which is slightly higher than the world average of 54% but still considerably below the urbanization rate of 78.3% for developed countries.

million migrants and other permanent urban residents to obtain urban household registration within the planned period.[3]

The contribution of this paper is threefold. First, previous studies of the relationship between energy intensity and urbanization (Jones, 1991; York, 2007; Jiang and Lin, 2012; Sadorsky, 2013) have tended to use only one indicator of urbanization which is usually the urban population rate measured as urban population divided by total population (Urban1). In this paper an additional measure is employed that takes into account China's "hukou" system. Since there are two categories of household IDs in China, namely agricultural households and non-agricultural households, there is some debate about whether those individuals that are considered to be part of the short-term floating population can be treated as part of the urban population (Zhang and Huang, 2010).[4] The household registration system that has lasted for more than 60 years has resulted in over 250 million rural migrants living in the cities without an urban "hukou" (NBSC, 2015). Although migrants provide low-cost labor they are perceived to receive unfair treatment in regard to the availability of public services and social welfare (e.g. education and health care). Based on the studies that examine the demographic measurement of urbanization (Liu and Liang, 1997; Zhu, 1998), urbanization is measured alternatively as the non-agricultural population divided by total registered population (Urban2) to reflect the formal urbanization level.

The second contribution is to investigate the different channels through which urbanization exerts an indirect impact on energy intensity. Based on previous studies (Jones, 1991; Madlener and Sunak, 2011; Sadorsky, 2013), four indirect channels have been identified,

[3]The huge movement of people from rural to urban areas underpinned the Chinese economic transformation but caused an appreciable increase in the share of city residents without urban *hukou*. Due to limited access to public services internal migrants have a lower average propensity to consume. The lower consumption of non-*hukou* households tends to impede progress towards a consumption-led growth model. According to Dreger et al. (2015) the current urbanization strategy in the absence of *hukou* reform is likely to dampen private consumption in China.

[4]According to Ru et al. (2012), 46.6 percent of the rural population is engaged in non-farming work and 13.4 percent are engaged in both agricultural and non-agricultural activities. For many agricultural households some degree of non-farming employment is now considered standard.

namely a construction pathway, a transportation pathway, an industry upgrade pathway and a residential consumption or lifestyle pathway. However, there has been no previous empirical validation of the magnitude of each of these channels on energy intensity.[5] In this study the indirect effect of urbanization is investigated extensively based on two energy resources (coal and electricity).

The third contribution, following Sadorsky (2013), is to control for heterogeneity across the unit of analysis using two different mean group estimators. Controlling for heterogeneity is important given the considerable variation in the economic development, resource endowments and climate across China's 31 mainland provinces. Such an approach is needed because the strict assumption of parameter homogeneity required for classical regression models is unlikely to hold across Chinese provinces. Moreover, because energy related policies are managed by the central government it is likely to have cross-sectional dependence within the province level panel. Hence, standard panel techniques will tend to produce biased and inconsistent results. More specifically, the extended version of the Mean Group estimator, the Augmented Mean Group (AMG) estimator (Eberhardt and Teal, 2008) is employed that takes both heterogeneity across parameters and common factors into account.[6]

To briefly preview the results, it is shown that urbanization exhibits a positive direct impact on energy intensity generally. Urbanization measured by the "hukou" system has a significant impact on the total energy intensity while urbanization measured by the percentage of the floating urban population shows a positive and significant direct impact on coal consumption intensity and electricity consumption intensity. A one percentage point increase in urban-

[5]One exception is Norman et al. (2006) who, based on a case study of Toronto, investigate the performance of three major elements in high and low residential density areas. In this case, construction and transport related energy use and greenhouse gas emissions are both higher in low residential density areas.

[6]Zhang and Lin (2012) estimate the impact of urbanization on energy consumption and CO2 emissions using a province level panel. They estimate a fixed effect model with Driscoll-Kraay standard errors which is argued to be robust to general forms of cross-sectional and temporal dependence (Hoechle et al., 2007). Although they consider regional differences (dividing China into three regions), the results may still suffer from panel heterogeneity concerns.

ization based on the floating population is shown to increase coal intensity and electricity intensity by 1.5% and 0.8% respectively. As for the indirect channels, they turn out to be negative or insignificant determinants of energy intensity. The indirect effect through the construction sector is shown to be the most significant channel. Transportation and industrial upgrading are found to be significant determinants but only under certain circumstances. Different lifestyles, whether in high or low urbanized areas, appear to have a similar contribution to aggregate energy intensity when taking into account cross-sectional dependence and province level heterogeneity. Other covariates such as income per capita and industrialization tend to play more important roles than urbanization in affecting China's provincial energy intensity perhaps as a result of the negative impact of the indirect urbanization channels. Income per capita has a negative and stable influence on energy intensity while industrialization has the expected positive effect. In terms of the two urbanization proxies, the informal measurement based on floating urban population generally affects energy usage through the first three channels while the formal measurement of urbanization based on the "hukou" system tends to affect energy usage through the construction and transportation pathways.

The remainder of the paper is organized as follows. Section 2 discusses the mechanisms by which urbanization, income and industrialization are expected to impact on a country's energy intensity. Section 3 presents the methodological approach while Section 4 provides a summary of the data. The results are presented in Section 5 before Section 6 concludes.

2.2 Literature Review

In this review of the literature we concentrate on the impact of urbanization on energy efficiency but also comment on the impact of industrialization and income of energy efficiency.[7] Overall the empirical studies have reached a mixed conclusion on the impact of urbanization. The results vary from country to country. Loosely speaking, urbanization has positively contributed to the rising energy demand in China during recent years. Most of the China-specific studies have focused on the aggregated energy usage or efficiency without specifying impact pathways. The existing literature generally agrees that income has a significant impact on energy intensity, which tends to be a non-linear inverted U-shape relationship. As for industrialization, the majority of the current research finds a positive relationship between industrialization and energy consumption.

2.2.1 The impact of urbanization on energy intensity

According to the 2012 UN Environment Programme (UNEP, 2012), urban areas, which currently occupy around 3% of the world's surface area, were estimated to consume approximately 75% of the natural resources and account for 60-80% of all greenhouse gas emissions. Urbanization can impact energy use through direct and indirect channels. The direct impact refers to the straightforward effect that urbanization exerts on energy use. The seminal study from Jones (1989) demonstrates that energy consumption increases as a result of, not only income per capita and industrial structure, but also the rate of urbanization. The elasticity of income per capita, industrialization and urbanization with respect to energy use were estimated to be 1.10, 1.08 and 0.48 respectively. Jones (1991) went on to investigate the direct mechanism by which urbanization impacts energy use employing similar cross-sectional data and found the long term urbanization elasticity to be 0.35. Similarly, Parikh and Shukla

[7] I conduct the literature search using *Google Scholar* combined with *Findit@Bham* which provides access to major bibliographic databases such as *EconLit* and *Elsevier*. I limit my search to academic journals and books. To stay focused on the research question and avoid redundancy, I revise my search by using more precise terms (e.g. *energy intensity* instead of *energy efficiency*), adding in limits (e.g. *China* and *energy intensity* and *income per capita*), and concentrating on key journals (e.g. *Energy Economics*) and authors (e.g. *Pesaran MH*). I often find it very helpful to examine how authors in the discipline have composed their literature review sections. For example, the structure of the literature review in the present study shares similarities with those of Jones (1991) and Sadorsky (2013).

(1995) estimate the relationship between urbanization and increasing resource consumption for a range of developing and developed countries between 1965 and 1987 and find that the elasticity of energy intensity with respect to urbanization is 0.47. Likewise, York (2007) and Rafiq et al. (2016) find similar effects with significant and positive elasticities for urbanization for the 14 EU countries and 22 emerging countries respectively.

In contrast, other papers have found that under certain conditions urbanization can have a negative direct impact on energy consumption. Martínez-Zarzoso and Maruotti (2011) find an inverted U relationship between CO2 emissions and urban population density for half of their developing country sample with a threshold effect for urbanization's impact where once a threshold has been reached, further urbanization does not result in greater emissions. Everything else equal, they find the highest emission levels come at an urbanization level of 59% to 63% (which compares to China's current level of around 54%). More recently, Zhu et al. (2012), in a study of 20 emerging countries between 1992 and 2008, finds little evidence of an inverted U-shape relationship between urbanization rate and CO2 emissions. Others have argued that the impact of urbanization on energy consumption varies considerably depending on the level of development. Mishra et al. (2009) examine nine Pacific Island countries and find that urbanization affects different economies in opposite directions while Poumanyvong and Kaneko (2010) find that although urbanization appears to exert a negative impact on energy use for low-income groups it is positive for middle- and high-income country groups. From the perspective of ecosystem integration, Long et al. (2016) finds that urbanization has a potential to decrease the ecological footprint associated with increased income.

For China specifically, a number of studies examine the direct relationship between energy consumption and urbanization (Jiang and Lin, 2012; Liu, 2009; Zhang and Lin, 2012; Ma, 2015; Yan, 2015). For example, Jiang and Lin (2012) show that trends in industrialization and urbanization predicts that China's energy demand will keep rising until 2020. In terms of urbanization, Liu (2009) finds unidirectional Granger causality from urban population density to total energy consumption although the contribution from urbanization tends to be smaller in the later years of the sample. At the province level, Zhang and Lin (2012) show that urbanization has a positive effect on both energy consumption and CO2 emissions although when they take China's unbalanced regional development into account they find that energy consumption decreases dramatically as one moves from the western to the eastern provinces.

More recently, Ma (2015) finds that urban infrastructure to be a major determinant of the positive short-run relationship between urbanization and energy intensity, while the long term increase in energy use associated with urbanization is driven by residential consumption patterns and urban transport systems. Although Ma (2015) touches on the transport, residential consumption channels, the effectiveness and magnitude of each is not examined in any detail. Finally for China, Yan (2015) also uses province level data and finds a positive and significant impact of urbanization on both aggregate energy intensity and disaggregate energy intensity with the elasticities ranging from 0.111 to 0.287 for the proportion of the population that is urban and from 0.269 to 0.350 for the proportion of the population that is non-agricultural.

Turning to the indirect channels by which urbanization impacts energy efficiency, several have been identified by Jones (1991) and Madlener and Sunak (2011) and summarized by Sadorsky (2013). The arguments are briefly rehearsed again here. The first indirect channel is the need for growing cities to absorb ever increasing volumes of high energy intensive products such as steel and cement. Urbanization means additional demand for building stock and other infrastructure resulting in inner-city clustering and land shortages which can lead to a greater use of multilevel building (Parikh and Shukla, 1995). Office buildings, power plants, sewage networks are generally accompanied by significant ongoing energy inputs. Likewise, the maintenance of completed infrastructure projects tends to be energy hungry. In addition, in developing countries, the process of urbanization is often associated with the uncontrolled diffusion of informal settlements and illegal housing which are usually inefficient in their use of energy, even though informal dwellings (e.g. shanty towns) often lack access to basic amenities including electricity.

The second channel is that as the scale of urban production increases, raw materials need to be transported from their often rural origin to the urban production center and final goods in turn need to be transported to the destination of consumption which is likely to be other urban conurbations or overseas. Urbanization also increases intra-city mobility which causes the emissions of various pollutants especially in developing countries where the basic transit infrastructure is generally poor leading to the greater use of private trucks and automobiles.

Thirdly, urbanization is associated with a concentration of economic activity and hence an increase in urban production. When people move to the city from rural areas the result is that more human resources are absorbed by the relatively more energy intensive secondary and tertiary sectors. The decline in the agricultural population can also lead to an increasingly mechanized and more energy intensive agricultural production process (Jones, 2004). In addition, in those countries that have a large informal market where economic activities are neither taxed nor registered, energy consumption can rise (Schneider and Enste, 2000). Counter balancing these effects is the notion that rising competitive pressures and land scarcity tends to drive urban production to be more innovative and to use modern and more technologically advanced capital which is likely to be more environmental friendly (Jones, 1989).

Finally, a forth channel by which urbanization impacts energy intensity is through the change in lifestyle and consumption patterns of the newly urbanized citizens who tend to be more dependent on certain energy intensive products such as air conditioners, refrigerators and private vehicles (Jones, 1989). Increasing disposable income also increases the likelihood that households will purchase more electrical appliances. In addition, urban dwellers are more likely to derive their energy from coal or natural gas and not from decentralized sources of energy such as wood.

Although the previous literature discusses the indirect mechanisms by which urbanization impacts energy intensity, few provide a systematic assessment of these different channels. One exceptions is Liddle (2003) who finds that densely populated countries tend to have a lower personal vehicle demand. Similar results are found for an input-output life cycle assessment model for Toronto (Norman et al., 2006). Transportation-related greenhouse gas emission per capita are estimated to be 3.7 times higher from low residential density areas. The rank-size relationship is also true when considering the embodied energy and pollutants from the construction industry.

With regard to lifestyle and residential energy consumption, Krey et al. (2012) focus on urbanization in China and India using an integrated assessment model and show that total consumption of fossil fuels in the residential sector is not sensitive to urbanization arguing that it is the evolution of labor productivity induced by urbanization that really matters. O'Neill et al. (2012) finds similar results for China and India using a computable general equilibrium (iPETS) model. Minx et al. (2011) employ a structural decomposition approach to examine Chinese carbon dioxide (CO2) emissions and finds increasing export demand and structural changes to be the largest contributors to CO2 emissions with capital investment accounting for 61 percent of emission growth between 2005 and 2007. The effect of urbanization and the related evolution of lifestyles are shown to be more significant than other social-demographic factors such as population and household size with the overall emission effect of urbanization still coming out as positive even after netting out the potential carbon savings due to economies of scale. Finally, Wang (2014) examines different types of energy consumption and finds that urbanization reduces residual energy consumption per capita but substantially increases aggregate energy consumption.[8]

2.2.2 The impact of income per capita on energy intensity

A number of studies that examine the relationship between income and energy consumption with mixed results. Malenbaum (1978) was the first to show resource intensity changing with income. Galli (1998) in turn estimated the long-term relationship between energy intensity and income for ten Asian emerging countries across 28 years and found a negative and significant coefficient for the squared income term. Using spatial econometric techniques, Maddison (2006) found a monotonic relationship between income and greenhouse gas emissions based on a two-year panel from 136 countries. Zhao and Fan (2008) examined the relationship between growth and energy consumption for different Chinese regions using a smooth transfer regression (STR) estimation and found a stationary nonlinear relationship even during different developing phases. A recent study by Song and Zheng (2012) shows that although the evaluation process of China's energy intensity follows a U-shape, the turning point is higher than 95% of the sample meaning that for most years, energy intensity follows a declining trend with regard to GDP per capita. Jiang et al. (2014) find similar results showing that for 19 out of 29 provinces between 2003 and 2011, energy intensity fell with the growth of income. In contrast, Shao and Jia (2006) and Liu (2007) find no strong causal relationship between Chinese economic growth and the energy consumption.[9]

[8] In a related literature, Khanna et al. (2013) examine the local enforcement of two of China's recent energy efficiency policies based on household appliances across several pilot locations between 2006 and 2009. They generally find high compliance but with a large variation with insufficient organizational coordination between government agencies and the low priority given to energy efficiency in national quality testing as the main challenges.

[9] Bernardini and Galli (1993) examine the long-term trend in energy and materials consumption intensity with energy intensity being determined by three main factors and helps to explain the non-linear results found in other papers. First, energy consumption is driven by income because of changes in the final demand structure

2.2.3 The impact of industrialization on energy intensity

Industrialization, which refers to the process by which a society transforms itself from a traditional agricultural society to one based on higher value added manufacturing, means that mechanized mass production and assembly lines are used to replace craftsmen and individual manual labor. The result is higher energy consumption driven by certain heavy industries (for example ferrous and nonferrous metals processing, petroleum refining and paper and allied production). Sadorsky (2013)(Sadorsky 2013) finds in the long-run that a 10% increase in industrialization causes a 0.7% to 1.2% increase in energy intensity. Feng et al. (2009)(Feng et al. 2009) who investigate the long-term relationship between economic structure, energy consumption and energy intensity between 1980 and 2006 for China find that economic structure Granger causes energy intensity.

To explain the impact of industrialization more precisely, Fisher-Vanden et al. (2004), Ma and Stern (2008) and Liao et al. (2007) divide the economic structure of a country into a number of sub-sectors and identify structural and efficiency effects. Liao et al. (2007) find an efficiency effect where the role of technology is considered to be the dominant contributor to the change in energy intensity. Structural change at the industry level increases energy intensity while structural shifts between sub-sectors decreases overall energy intensity (Ma and Stern, 2008). Using a panel of approximately 2,500 large and medium-sized industrial enterprises between 1997 and 1999, Fisher-Vanden et al. (2004) demonstrate that the efficiency effect plays an important role in reducing energy intensity at the firm-level and accounts for 47% of the

so that energy intensity follows a bell shape such that energy intensity rises and then declines as the economy passes from the pre-industrial to industrial and on to a post-industrial stage. In pre-industrial communities energy intensity is relatively low because of the dominant agriculture sector. As industrial growth accelerates it is accompanied by the rapid development of infrastructure. Further increases in income per capita then induces high energy-consuming lifestyles until material demand reaches saturation point. Finally, in the post-industrial there is a decline in energy intensity as an economy makes the transition to a less energy intensive service sector economy.

decline. For the service sector in the OECD Mulder et al. (2014) argue that structural changes had an increasingly important effect on aggregate energy intensity especially after 1995.

Advances in technology can also make production more environmental friendly. In China, non-state and foreign investment has also had a significant impact on the diffusion of energy-saving technologies Herrerias et al. (2013). The cleaning effect of new technology is also found by Garbaccio et al. (1999) who finds that technical change within an industry is the main driver of a declining energy-output ratio (with structural change increasing energy consumption).

2.3 Methodology

The empirical approach of this paper follows Sadorsky (2013) who uses Jones (1991) original estimating equation to enable us to estimate the relationship between three measures of energy intensity and income per capita, industrialization and two alternative measures of urbanization. The estimating equation (in logs) is therefore given by:

$$EI_{it} = \alpha + \beta_{1i}YPC_{it} + \beta_{2i}IND_{it} + \beta_{3i}URBAN_{it} + \xi_t + \upsilon_i + \varepsilon_{it} \tag{2.1}$$

The subscripts i and t denotes a province and year respectively. The dependent variable EI_{it} is either total energy intensity (TEI), coal energy intensity (CEI) or electricity energy intensity (EEI). The right hand side variables are measures of income per capita (YPC), industrialization (IND) and the measures of urbanization (Urban1 and Urban2). ξ_t captures year fixed effects and υ_i captures province fixed effects. ε_{it} is the error term.

Using logs and assuming the error term ε_{it} is distributed with zero mean and constant variance-covariance matrix the coefficients can be interpreted as elasticities. One concern however is that classical panel regression techniques could produce misleading and inconsistent results because of the homogeneity assumption across provinces. Under the homogeneity assumption pooled OLS and various fixed effects specifications impose the condition that $\beta_{1i} = \beta_1$, $\beta_{2i} = \beta_2$, $\beta_{3i} = \beta_3$ and negates the possibility of individual panel specificity. In this case, this is a concern because the variables are measured at the province level where there are considerable differences in growth and development between the coastal and inland provinces.

The ideal solution to address this possible source of bias is to estimate β_{1i}, β_{2i}, β_{3i} separately. A starting point is to use the standard Mean Group (MG) estimator developed by Pesaran and Smith (1995). The β coefficients are estimated separately for each province and the simple arithmetic average is taken. For $i = 1,2,3\ldots N$, $t = 1,2,3\ldots T$, let:

$$EI_{it} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{X_{it}} + \varepsilon_{it} \tag{2.2}$$

$$\hat{\boldsymbol{\beta}}_{MG} = N^{-1} \sum_i \hat{\boldsymbol{\beta}}_i$$

where β_i is the panel specific coefficient vector and X_{it} is the vector of independent variables including YPC_{it}, IND_{it} and $URBAN_{it}$ where subscript i represents an individual province.

Although Mean Group (MG) estimators can account for parameter heterogeneity they are still based on the assumption of cross sectional independence. If the assumption fails to hold then the MG estimation procedure will lead to biased and inconsistent results. To address this problem Eberhardt and Teal (2008) developed the Augmented Mean Group (AMG) estimator which takes into account both parameter heterogeneity and possible cross-sectional dependence. The AMG estimator includes a “common dynamic process” extracted from a pooled OLS regression of first differences which provides a panel-equivalent average movement of the unobserved common factors. Common factors are those that are time specific and common across provinces. The AMG approach follows a two-stage procedure;

$$\Delta EI_{it} = \boldsymbol{\beta_i'} \boldsymbol{\Delta X_{it}} + \sum_{s=2}^{T} c_s \Delta D_s + \Delta e_{it} \tag{2.3}$$

$$\Rightarrow \hat{c}_s \equiv \hat{\mu}_t^*$$

$$EI_{it} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{X_{it}} + \kappa_i \hat{\mu}_t^* + e_{it} \tag{2.4}$$

$$\hat{\boldsymbol{\beta}}_{AMG} = N^{-1} \sum_i \hat{\boldsymbol{\beta}}_i$$

In the first stage (Equation 2.3) we estimate a standard first difference OLS regression with $T-1$ year dummies denoted by D_s. The coefficients on the year dummy $\hat{c}_s$ are recorded and relabeled as $\hat{\mu}_t^*$. In the second stage (Equation 2.4) the variable $\hat{\mu}_t^*$ is included to represent the evolution of the unobservable common factor over time.[10]

To identify the channels by which urbanization impacts energy intensity we also include in our estimating equation the energy intensity of different sectors and the corresponding interaction term. The estimated coefficients on the interaction terms capture the direction and magnitude of the indirect impact of urbanization on energy intensity. A significant interaction term implies that the intensity contribution from that subsector is dependent on the level of

[10] An alternative to the AMG approach is to use the Common Correlated Effects (CCEMG) estimator developed by Pesaran (2006) and used by Sadorsky (2013) which also takes into account both parameter heterogeneity and common factors. This CCEMG has a general multifactor error structure and assumes that the unobservable common factor can be substituted by the cross-sectional average of the independent and the dependent observations. Compared to the AMG approach, the CCEMG estimator is relatively data-intensive since the degrees of freedom are reduced considerably after the inclusion of the averages as proxies for the unobservable common factor in each region regression. In relatively short province time-series this could lead to loss of precision in the province estimates. With panel data, N is regarded as infinite asymptotically and T is finite. Since we have a relatively short panel the CCEMG approach is unreliable. For reasons of completeness we present the CCEMG results in the appendix.

urban development. Our estimating equation is therefore:

$$\begin{aligned} EI_{it} = &\alpha + \beta_{1i} YPC_{it} + \beta_{2i} IND_{it} + \beta_{3i} URBAN_{it} + \beta_{4i} SUB\_EI_{it} \\ &+ \beta_{5i} URBAN_{it} \times SUB\_EI_{it} + \xi_t + \upsilon_i + \varepsilon_{it} \end{aligned} \tag{2.5}$$

The subsector intensity SUB_EI_{it} is calculated by measuring CEI/EEI for the construction, transportation, tertiary and residential sectors. Detailed definitions can be found in Table A.1 of the appendix.[11]

2.4 Data

2.4.1 Data description

In this paper we use a balanced panel for 30 Chinese provinces for the period 1995 to 2012.[12] The original data are obtained from China Statistical Yearbooks, China Population Statistical Yearbooks and China Energy Statistical Yearbooks. In the following empirical analysis, total energy intensity (TEI) and two specific energy intensity variables, namely coal intensity (CEI) and electricity intensity (EEI) which are measured by energy consumption per real GDP, coal consumption per real GDP and electricity consumption per real GDP respectively. Energy intensity in construction and tertiary sector is defined as the energy consumption (coal or electricity) in that sector divided by the real value added in that sector while the

[11] Year dummies are included in all classical estimations. With the mean group (MG) estimations, a linear trend term was included but none were significant at the 95% level. Since the time effects tend to be nonlinear, the linear trend term is negated. In the augmented mean group (AGM) estimator, $t-1$ year dummies are taken into account automatically in the first stage of the estimation procedure.

[12] We exclude Tibet from our analysis since it contains only a small numbers of observations and has extreme high values of energy intensity due to the low real GDP. We also use linear interpolation to account for the boundary change for Chongqing (which was separated from Sichuan province to become a municipality in 1997).

denominator for transportation and residential energy consumption (coal or electricity) is the total population at year end. Income per capita refers to the real gross domestic product per capita and industrialization is measured as the industrial value added divided by GDP.[13] We include two measures of urbanization (discussed in more detail later). First, we divide the percentage of the population living in urban areas by total province population at year end (Urban1). Second, we divide the percentage of non-agricultural population by the number of people registered in the province (Urban2).[14] Table A.2 provides a simple correlation matrix for our main variable of interest. The raw data suggest a negative correlation between total energy intensity and income per capita, industrialization and urbanization.

Figure 2.1 presents the provincial average trend in China's energy intensity between 1995 and 2012. Both aggregate energy intensity and coal intensity in China reversed its previous decline and rose slightly in 2003 before resuming its gradual decline. The electricity intensity is relatively stable. Table 2.1 provides a summary of our key variables for each of China's 30 provinces between 1995 and 2012. The heterogeneity across provinces is evident with aggregate energy intensity ranging from a low of 0.816 in Guangdong to 3.428 for Ningxia. The industrialization and urbanization variables have a lower variance although Beijing still has an urbanization rate that is more than double that of many of the other provinces in China.

[Figure 2.1 about here]

[13] Industrialization has also been measured as the ratio of secondary sector value added to GDP (Jiang and Lin, 2012; Jiang et al., 2014). Although the definitions are slightly different in our case the correlation between the two measures is 0.98.

[14] It is necessary to distinguish between different statistical definitions of population in China. The denominator for Urban1 is the population at year end (Changzhu renkou) and is defined as the number of long-term residents living in a specific region, including the local registered population but not including those that leave the area for more than half a year, people registered in other places or people never registered in one place but live in a region for more than half a year. The denominator for Urban2 is the registered population (Huji renkou) which is defined as the population who are registered in the hukou system. An individual with a hukou registration in a local area is counted whether they live locally, or even if they leave for a half year or more (Liu, 2004).

[Table 2.1 about here]

Table 2.2 provides data descriptive for our key variables for each of China's 30 provinces. It shows that income per capita grew by an average of 11.2% a year while energy intensity fell by an average of 3.7% a year. The decline in coal intensity averages 6.3% a year which is a lot faster than that for electricity intensity which declined by just 1.3%. At the same time industrialization increased by an average of 0.78% a year. The average annual growth rates for urbanization indicators Urban1 and Urban2 were 4.3% and 2.5% respectively.

[Table 2.2 about here]

Figures A.1, A.2 and A.3 in the Appendix show the trends in urbanization, industrialization and income per capita for the period 1995 to 2012. Both urbanization indicators have increased over time while the growth of Urban2 is smoother than Urban1. Figure A.2 shows industrialization was relatively stable until 2002 when it experienced rapid growth before declining as the global economic crisis of 2008/2009 impacted the Chinese economy before resuming its upward trajectory. Figure A.3 shows that income per capita continued to rise throughout this period.

2.4.2 Formal and informal urbanization

Studies that distinguish between formal and informal urbanization in China date back to the nineties. For example, Liu and Liang (1997) provide a detailed case study of the informal urbanization on the fringe of Beijing. In addition to political, cultural and social reasons, economic factors are regarded as some of the most important determinants of rural-urban migration. Zhu (1998) argues that the distinction between formal and informal urbanization is important to understand the urbanization process in China and provides a precise definition of formal and informal urbanization. The formal urban population refers to the de jure urban citizens who have the non-agricultural hukou registration while the informal urban population also includes some de facto urban inhabitants that consist of the floating population that have arrived from other areas as well as local residents that only hold the agricultural hukou registration even if they are involved in non-agricultural activities. These temporary residents tend to have no access to a range of benefits and privileges available to urban residents, they tend to work in the industrial sector, have poor living conditions and relatively high migration frequency.[15] According to the China Household Finance Survey, urban residents holding agricultural hukou registration account for one quarter (25.3%) of the total population during 2009 to 2013. The proportion is considerable large comparing with 29.3% of urban residents holding non-agricultural hukou registration (Gan, 2014).

Due to the important difference in social and economic status between the floating population and local residents we make the distinction between measures of urbanization based on hukou registration from one based on the urban floating population. The only other study that examines the relationship between migration and energy is Yan (2015) who uses the ratio of non-agricultural population to total population as the robustness check for the urban area population. Table 2.3 provides the annual average population based on these two definitions from 1995 to 2012. At the first glance one can observe that the urban population is consistently higher than the non-agricultural population that is currently registered in that province. The difference between the floating population and local citizens is the agricultural population that have arrived from rural areas and other non-agricultural people from other cities. Guangdong, and Zhejiang have the largest recorded difference between the two

[15]Shen (2002) examines migration patterns and concludes that migrants from within a province have an employment advantage over those from other provinces. In both cases migrants tends to live in company quarters (31.4%), rented housing (29.3%) and construction sites (15.8%). The accommodation situation has improved in recent years according to the urbanization and labour migration survey conducted by Tsinghua University (2013). Approximately 21.6 percentage of temporary residents with agricultural hukou now own private property in urban areas above the county level, while 79.8% of non-agricultural floating population have their own property.

measures and considered to the largest hosts for migrants during our period of analysis, a finding that matches that of Zhang and Song (2003).[16]

2.5 Empirical Results

Before we present our results it is useful to note that classic panel unit root tests which do not take cross-sectional dependence into account can be misleading (low power). Standard unit root tests can over reject as a consequence of considerable size distortion (Baltagi et al., 2007).[17] Hence, Pesaran (2007a) developed the CIPS test (Cross-sectional Im-Pesaran-Shin test) for stationarity that can also be used as a test for cross-sectional dependence. Table 2.4 presents the CIPS test and the Pesaran (2004) CD test for cross-sectional dependence for each of our variables. The p-values in the second column of Table 2.4 show that each of our series rejects the null hypothesis of cross-sectional independence except CEI in transportation industry. The CIPS test which contains two lags, a trend term and an intercept also indicates that the series include a unit root. When we are searching for an appropriate model to test our hypothesis we are looking for a high p-value for the CD test and a low p-value for the CIPS test. Our results at this stage are similar to those of Sadorsky (2013) whose data also exhibit cross-sectional dependence with each series containing a unit root.

[Table 2.4 about here]

To investigate the relationship between urbanization, industrialization, income per capita and energy intensity we estimate a series of models under different assumptions. Tables 2.5 and 2.6 present the results using pooled OLS and simple fixed effects models to benchmark our

[16]Zhang and Song (2003) find that at the end of 1998, Guangdong, Zhejiang, Fujian and Jiangsu were the top four migration host provinces. In Table 2.3, Jiangsu ranks in 6th place while Fujian is in 10th place.

[17]The power of a binary hypothesis test is the probability of rejecting the null when it is false, which is related to type II error. The size of a test is the probability of falsely rejecting the null hypothesis, which is related to type I error.

results against those of previous studies. Three types of energy intensity are investigated, namely total energy intensity (TEI), coal energy intensity (CEI) and electricity energy intensity (EEI). Table 2.7 presents our mean group estimations that take into account cross-sectional dependence while Table 2.8 presents the results from the AMG estimations that allow for both cross-sectional dependence and heterogeneous slope parameters. Finally, Tables 2.9 to 2.12 present our indirect results where we examine the four channels by which urbanization may have an indirect impact on energy usage. Year dummies are included and all models are estimated with robust standard errors. As part of a series of robustness checks all models were reestimated including quadratic terms (which were nearly always insignificant and hence not reported) and using our alternative measure of industrialization (secondary sector value added divided by GDP) which gave quantitatively and qualitatively similar results.

Table 2.5 reports the pooled OLS results which reveal a consistent negative and significant effect of income per capita on energy intensity. The coefficients of income per capita estimations range between -0.803 and -1.517 with the impact being larger for the energy intensity of coal (CEI). The results also show that industrialization is a strong positive determinant of energy intensity and the coefficient is significant across all specifications with relatively stable elasticities ranging between 1.696 and 3.517 across all six models. Since coal is an important input into the process of industrialization, the marginal impact of industrialization on energy usage is consistently stronger for CEI. For urbanization we find a positive and significant impact for both of our urbanization measures. The coefficients range from 1.345 to 2.255, which implies that a one percentage point increase in urbanization would induce a 1.345% to 2.255% increase in energy use considering other variables at a constant level.

In Table 2.6 we include province fixed effects. The results are broadly similar although the magnitude of the effects are now smaller. Concentrating on urbanization, the coefficients for the fixed effects estimations range from between 0.875 and 1.126 which are consistent with Zhang and Lin (2012) who find an urban impact of 0.41 and Ma (2015) who presents an impact range from 0.20 to 0.29. The Urban2 and Urban1 results are broadly similar.

[Table 2.5 about here]

[Table 2.6 about here]

The difficulty with the results presented in the previous two tables is that under the null hypothesis of cross-sectional independence, all p-values associated with the CD test for TEI and CEI reject the null hypothesis which means there is a problem of cross-sectional dependence. The fact that electricity use suffers less from cross-sectional dependence might be due to the multiple power generation approaches and well-developed power distribution and transmission network occupied by the State Grid Corporation of China (covering 88% of Mainland China) and China Southern Power Grid Company Limited (covering Guangdong, Guangxi, Yunnan, Guizhou and Hainan). Equally problematic is that the CIPS test results suggest that the fixed effects regressions are poorly fitted due to non-stationary residuals. Our first attempt to address these concerns is to use mean group (MG) model the results of which we present in Table 2.7.

[Table 2.7 about here]

The results in Table 2.7 show that the coefficients on income per capita and industrialization remain statistically significant at the 1% level (with the exception of the coefficient on industrialization in column (6) which is now insignificant). Income per capita is again negative and industrialization appears to have a large impact on the use of coal. Urbanization continues to have a positive impact on energy intensity in three of our six specifications.

The coefficients on both income per capita and industrialization are now much smaller than those of the OLS regressions in Table 2.5 but consistent with those from the fixed effect model in Table 2.6. In contrast to what we found in previous tables, all the MG regressions have stationary residuals according to the CIPS test. However, the CD test results continue to suggest that we have an issue with cross-sectional dependence. Hence, in Table 2.8 we present the results from our augmented mean group estimations and are our preferred specification.

[Table 2.8 about here]

The coefficients on income per capita shown in Table 2.8 remain generally negative and significant at the 5% level. The coefficients range from -0.29 to -0.81 which is consistent with the elasticities found by Sadorsky (2013) who estimates a range of elasticities from -0.57 to -0.53 and -0.45 to -0.35 for the short run and long run elasticities respectively. The income elasticities for EEI are larger than those of CEI implying that provinces with higher income per capita tend to consume electricity more efficiently. Returning to industrialization, under the AMG specification, we find it to be insignificant in four out of six regressions. The significant coefficients are also smaller than those of our previous tables and are now consistent with the findings of Ma (2015) which is 0.217 although slightly higher than the long-run effect of 0.07 to 0.12 found by Sadorsky (2013) who looks at developing countries more generally. Considering the disaggregated energy types, urbanization (Urban1) has a positive and significant impact on CEI and EEI at the 5% level (Column (2) and (3)). In each case the AMG models pass both tests which gives us greater confidence in our findings. The results suggest that the impact of urbanization on energy intensity is not as clear cut as may have initially thought from the OLS and FE regressions.

To further examine the various channels though which urbanization has an impact on energy use we now include interaction terms of sector energy intensity and our measures of urbanization. Our four sectors are (1) Construction; (2) Transport, storage and post; (3) Wholesale, retail trade, hotel, and restaurants; and (4) Residential consumption. The results are shown in Tables 2.9 to 2.9 using both MG and AMG approaches for our three types of energy intensity and two urban indicators.

Table 2.9 presents our analysis of the construction channel. Both the energy intensity in the construction sector and its interaction term with our urban indicators are included . It is reasonable to assume that the energy intensity at the sector level will make a positive contribution to aggregate energy intensity. As a result, both CEI and EEI in the construction sector have positive coefficients at least at the 10% significant level. According to Parikh and Shukla (1995), the process of urbanization tends to be accompanied by increased building and other infrastructure activities. However, the interaction terms between our urban indicators and energy intensity in the construction sector also show a significant and negative impact on both types of energy intensities. This suggests that in those provinces that have higher urbanization levels, the contribution to energy intensity from the construction sector to aggregate energy intensity is lower than that in the less urbanized provinces. In other words, the construction sector uses energy more efficiently in already highly urbanized areas. Given the rapid rate of urbanization in China, the importance of energy conservation in the construction sector has become an important area of policy with the Chinese central government launching a serious of regulations and criteria targeted at the construction sector.

Returning to the results we find that the MG results still suffer from non-stationary residuals. Focusing on the AMG model (which passes both the CD test and CIPS test) the coefficients on the sector energy intensity and the interaction term obtained with Urban2 are generally larger (approximately 3 times) than those for Urban1. One possible explanation is that local residents with non-agricultural hukou have a better chance to purchase one or more houses. Therefore, through the construction channel, the model specification with Urban2 based on the hukou system would lead to a larger impact of urbanization. The income per capita variables remain a negative and significant determinant of energy intensity under the MG and AMG assumptions except in columns (2) and (6). However, the finding for industrialization suggests it only has a minor influence on aggregate energy intensity with the AMG specification showing only one out of four of the coefficients being significant at the 10% level.

[Table 2.9 about here]

The second channel where urbanization can have an impact is through the transportation sector. Energy consumption and emissions tend to raise substantially as intra-city and inter-city mobility increases. At first glance, the transport pathway that links urbanization and energy efficiency suggests an inverted relationship. Our results suggest that transportation tends to be more energy efficient in highly urbanized provinces. This is consistent with Norman et al. (2006) who shows that low density areas have relatively a lower number of public transit users. Furthermore, residents living in low density areas have a much higher vehicle dependency than those living in the city center. According to the CIPS test, the AMG specification results are more reliable where the urban impact pathway through the transportation channel found to be weaker. The coefficients for interaction terms in column (4) and (6) are significant at the 5% level implying that the transportation sector is less electricity/coal intensive in more urbanized areas when using Urban2/Urban1 as the measurement criteria respectively. As for the other control variables, income per capita remains generally negative and significant under both the MG and AMG specifications, while industrialization drops out in most of our AMG estimations.

[Table 2.10 about here]

As noted in the literature review, urbanization is associated with a concentration of economic activity. The usual process of development is from the primary to secondary to tertiary. In Table 2.11 we investigate the industry composition channel by including energy intensity in the tertiary sector and its interaction with urban indicators. Energy intensity in the tertiary sector is measured as coal or electricity consumption in wholesale, retail trade and hotel, restaurants subsectors divided by real value added in those subsectors. Column (1), (2), (4), (6) and (8) pass the CD and CIPS test at the 1% level which suggests cross-sectional independent and stationary residuals. The results show that coal consumption tends to be affected the most through this channel. In first two columns, not surprisingly we find that coal energy intensity makes a positive contribution to the aggregate coal intensity. The interaction terms have a negative and significant impact on aggregate CEI which implies that in highly urbanized provinces the contribution from the tertiary sector is lower than in less urbanized areas. However, the mechanism is less clear when we consider electricity intensity. Under this impact scenario, income per capita remains the most robust factor and all coefficients are negative and significant at the 1% level. The significance and magnitude of the income effect is fairly stable across all our channels in Tables 2.7 to 2.12, ranging from approximately -0.3 to -0.8. As for the industrialization variable, it performs differently for different energy types with coal use seemingly more affected than electricity use.

[Table 2.11 about here]

The final channel we investigate is lifestyle and residential energy consumption. Residual coal/electricity consumption per capita and its corresponding interaction term with our urban indicators are included in both the MG and AMG specifications. It is notable that under this channel, urbanization performs differently for each of our two energy types. More specifically, when we take the residential energy consumption into account, residential CEI and EEI are positively related to the aggregate intensity with the aggregate CEI seemingly more affected. The AMG estimation results are presented in columns (5) to (8) in Table 2.12. Both of our two urban indicators shows a negative impact on aggregate CEI although the interaction terms are insignificant. It implies a significant impact through the other channels and the insignificance of channel four. As for the other covariates, income per capita remains a negative and robust influence on both energy types, and industrialization increases energy intensity.

[Table 2.12 about here]

To summarize our results, for each of our four channels we find that only one of the four channels offers a robust explanation for how urbanization affects energy intensity. We find that energy use in the construction sector in highly urbanized areas tends to be more efficient relative to provinces with low urbanization levels. When considering specific urbanization measurement, Urban1 exerts significant impacts on aggregate CEI through construction channel and industrial upgrading, while Urban2 has indirect impacts on CEI through the construction and transportation channels. Electricity intensity tends to be affected only through the first two channels. It seems that the impact through the last three channels, namely transportation, industrial upgrading and residential consumption are not necessarily as large as expected. This may be due for two reasons. First, the four channels described in the literature are mainly based on the energy consumption amount rather than energy intensity. For example, urbanization is usually accompanied by increased transportation in the city area, while mobility in the city-country fringe tends to have a higher reliance on vehicle transport rather than urban mass transit (Norman et al., 2006). The concentration of economic activity also brings the opportunity for the more efficient use of energy. Based on the theory of industrial symbiosis, firms which are geographically close could form an industrial ecosystem by utilizing the waste materials from one production process into another. Both economic profits and environmental benefits are maximized via the cycling and reusing of resources such as water and energy citepChertow2008, VanBerkel2009. After standardizing by the real value added in each sector, using energy intensity is more meaningful since it measures the efficiency of energy use.

Secondly, disaggregating by energy type may be missing differences at a more disaggregated level. For example, industries such as transport, storage and post tend to be more petroleum intensive. As a result, this might explain our insignificant finding for coal/electricity consumption through channel two. As for the inconsistent performance of our two urban indicators, it may due to the difference between the measures. The household registration system that has lasted for more than 60 years has resulted in over 250 million rural migrants living in the cities without an urban “hukou” (NBSC, 2015). Although migrants provide low-cost labor they are perceived to receive unfair treatment in regard to the availability of public services and social welfare (e.g. education and health care). According to the National New-Style Urbanization Plan (2014-2020), the government intends to reform the household registration system to pay more attention to “people-centered” urbanization.

2.6 Conclusions

Using a balanced panel of 30 Chinese provinces covering the period 1995 to 2012 we investigate the impact of urbanization, income per capita, and industrialization on energy intensity. We employ recently developed econometric techniques to take into account the substantial heterogeneity across Chinese provinces. First and foremost, in this paper we show that the direct impact of urbanization on energy intensity is positive although not as strong as previous predictions. When we consider the indirect influence, four major impact channels are investigated and the results are in consistent with previous studies. More specifically, the indirect effect through the construction sector is shown to be the most robust impact channel whilst the industrial upgrading (sector change) and transportation pathways tends to be significant under certain circumstances. Different lifestyles around high/low urbanized areas are likely to have the same contribution to the energy intensity when we take the cross-sectional dependence and provincial heterogeneity into consideration. Two of our urbanization indicators also behave differently under certain circumstances which demonstrates the importance of distinguishing between informal and formal urbanization. Province level heterogeneity also proved to have a substantial influence on the estimation for China. The relationship between economic growth, industrialization and urbanization energy can be captured more precisely by taking heterogeneous parameters and common factors into account which we test for using the CD and the CIPS tests.

Our results show that for China, urbanization impacts on energy intensity through the direct and indirect mechanisms. Urbanization measured by the percentage of the floating urban population shows a positive and significant direct impact on both coal consumption intensity and electricity consumption intensity. One percentage point increase in Urban1 is predicted to increase CEI and EEI by approximately 1.5% and 0.8% respectively. The indirect effect of urbanization through the construction sector is generally negative significant and the magnitude of the impact is larger when based on a formal measure of urbanization (Urban2) than that from the informal one (Urban1). The interpretation of the interaction term between urban indicator and energy intensity in the construction sector is that in highly urbanized provinces the construction sector contributes less to the aggregate energy intensity level. In other words, the construction sector utilizes energy more efficiently in highly urbanized provinces. Similar results are found when we consider the transportation pathway and the industry upgrade pathway under specific circumstances. Energy consumption due to residents' consumption was shown to be an efficient channel through which urbanization impacts energy intensity.

With regards to income per capita, there is strong evidence that per capita real GDP affects energy intensity estimated using both classic and more advanced econometric techniques. The elasticity is relatively large for the pooled OLS and ranges from -0.8 to -1.5, whilst it is smaller and stable for the fixed effect and mean group related estimations. The elasticity for the direct effect ranges from -0.3 to -0.8 which is generally consistent with Sadorsky (2013) who estimates elasticities between -0.57 to -0.53 and from -0.45 to -0.35 for the short run and long run respectively. Our findings indicate that income per capita is one of the most important drivers of reductions in energy consumption and is in consistent with previous studies that also focus on China's provincial data (Song and Zheng, 2012; Jiang et al., 2014; Ma, 2015).

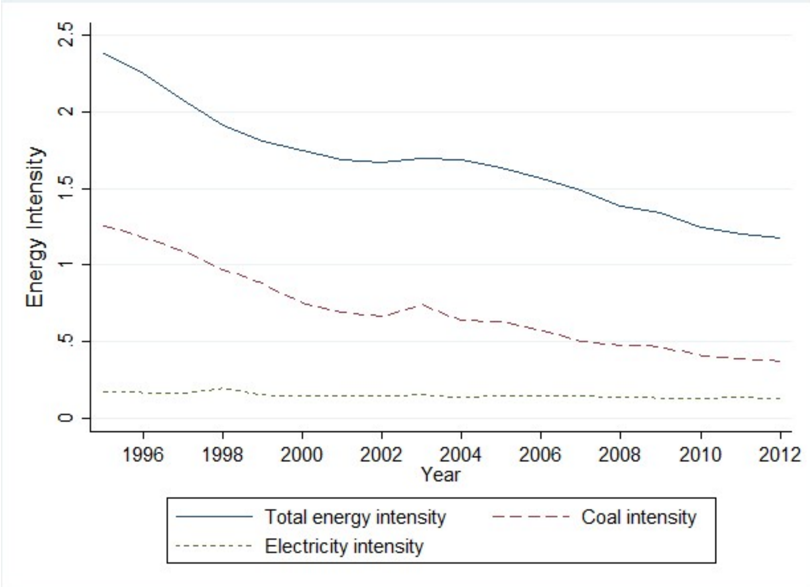
Industrialization is regarded to be one of the overwhelming contributors to China's economic growth. We find that energy intensity increases as the percentage of industrial value added rises. However, the impact of industrialization is not as strong as expected. It may due to the cleaner production benefiting from technology improvement (Garbaccio et al., 1999; Herrerias et al., 2013). Since accession to the World Trade Organization (WTO), the Chinese central government has launched a series of nation-wide policies focusing on energy conservation and emission reductions. These policies cover various aspects of secondary industry such as power generation and the manufacture sector. Increasing openness could also lead to the diffusion of energy-saving technologies. As a result, the positive effect of industrialization on energy intensity tends to be limited because of the active or passive technology change.

Although we have attempted to explain how the rate of urbanization impacts energy intensity more research is required. Improving energy efficiency is usually considered a practicable way to mitigate many common challenges such as climate change and possible energy shortages. The findings in this paper suggest a number of interesting policy implications.

First, the sensitivity of our results to the use of mean group techniques emphasizes the importance of provincial heterogeneity in China. Different geographical structures, nature features, energy storage and availability and even local culture and preference could all be part of the explanation. As a result, national targets need to be reconsidered taking into account local features. Identifying the inherent features of a region and implementing energy and environment policy at the local levels should be considered. Secondly, more attention should be given on the differences between informal urbanization and formal development. The urbanization rate as measured by the floating population surpassed the world average of 54% in 2014 (United Nations, 2014). Behind these numbers however are questions relating to the quality of the urbanization. Without basic infrastructure and urban planning, many urban areas in China are abandoned (so called ghost cities) while others consist of large numbers of high-rise buildings. Reform of hukou system will help to improve information management and optimize urban planning. Finally, policies to develop and plan for changes in industrial structure and technological upgrading need to be carefully considered. There is no doubt that urbanization and industrialization will continue for the foreseeable future despite the global slowdown in growth. Improving the efficiency of energy use may have a short term detrimental impact on economic growth but needs to be considered as part of a bigger picture to reduce urban air pollution and reduce China's dependence on imported energy. Finally, it is possible that the recent policy to encourage further urbanization may not have the negative impact on energy intensity and hence pollution that some expect. Equally, urbanization may not deliver the reductions in energy intensity that others might expect.

2.7 Figures and tables

Fig. 2.1 Chinese aggregate energy intensity, coal intensity and electricity intensity (1995-2012)



Source: China Statistical Yearbook 2013 (Units: tons of standard coal equivalent / RMB 10,000 in 2005 prices). The unit for coal intensity is tons / RMB 10,000 in 2005 prices and the unit for electricity intensity is kWh / yuan in 2005 prices.

Table 2.1 Energy, income per capita, industrialization and urbanization in China's 30 provinces (1995-2012) in 2005 prices

Province	Income per capita	Industrialization	Energy Intensity	Coal Intensity	Electricity Intensity	Urban 1	Urban 2
Shanghai	4.414	0.465	0.996	0.164	0.0981	0.783	0.804
Beijing	4.066	0.301	1.009	0.287	0.0865	0.809	0.726
Tianjin	3.459	0.528	1.312	0.446	0.108	0.709	0.593
Zhejiang	2.581	0.529	0.882	0.28	0.108	0.461	0.255
Jiangsu	2.446	0.531	0.915	0.316	0.103	0.459	0.393
Guangdong	2.327	0.485	0.816	0.191	0.105	0.53	0.425
Liaoning	2.023	0.498	1.89	0.567	0.137	0.551	0.478
Fujian	1.976	0.465	0.829	0.3	0.0995	0.434	0.277
Shandong	1.952	0.524	1.217	0.464	0.11	0.402	0.322
Inner Mongolia	1.896	0.44	2.162	1.097	0.163	0.466	0.374
Jilin	1.452	0.439	1.777	0.921	0.121	0.461	0.445
Hebei	1.412	0.507	1.937	0.878	0.145	0.329	0.251
Heilongjiang	1.395	0.516	1.692	0.504	0.114	0.54	0.47
Chongqing	1.388	0.473	1.266	0.741	0.109	0.439	0.265
Hubei	1.264	0.426	1.532	0.854	0.119	0.415	0.326
Xinjiang	1.246	0.417	2.32	0.905	0.128	0.372	0.389
Shanxi	1.226	0.52	3.327	1.332	0.221	0.394	0.293
Hainan	1.161	0.246	0.86	0.134	0.157	0.396	0.319
Shannxi	1.15	0.479	1.553	0.715	0.133	0.347	0.262
Ningxia	1.14	0.446	3.428	1.511	0.396	0.381	0.33
Hunan	1.119	0.401	1.311	0.73	0.0998	0.347	0.21
Henan	1.119	0.504	1.379	0.666	0.129	0.289	0.198
Sichuan	1.048	0.424	1.483	0.526	0.11	0.294	0.223
Qinghai	1.046	0.466	2.916	0.872	0.374	0.387	0.297
Jiangxi	0.987	0.436	1.059	0.505	0.0923	0.345	0.246
Jiangxi Anhui	0.95	0.422	1.345	0.882	0.109	0.329	0.206
Guangxi	0.92	0.387	1.154	0.554	0.121	0.309	0.182
Yunnan	0.813	0.426	1.603	0.634	0.141	0.261	0.162
Gansu	0.764	0.439	2.44	0.982	0.252	0.287	0.221
Guizhou	0.592	0.384	3.278	2.164	0.261	0.244	0.153

Notes: Data source China Statistical Yearbooks, China Population Statistical Yearbooks and China Energy Statistical Yearbooks. Income is the annual average real GDP per capita (10,000 RMB/person); Industrialization is the annual average secondary industry value added divided by GDP; Energy intensity is the annual average energy consumption per real GDP (tons standard coal/10,000 RMB); Coal intensity is the annual average coal consumption per real GDP (tons/RMB 10,000) and the electricity is the annual average electricity consumption per real GDP (kWh/yuan); The two urban indicators are urban population density and nonagricultural population density.

Table 2.2 Summary statistics for China's 30 provinces (1995-2012) in 2005 prices

Variable	Obs	Mean	Std. Dev.	Min	Max
Income per capita	540	1.638	1.379	0.217	7.416
Industrialization	540	0.386	0.081	0.121	0.53
Energy Intensity	540	1.659	0.866	0.48	6.47
Coal Intensity	540	0.704	0.532	0.059	3.38
Electricity Intensity	540	0.147	0.084	0.049	0.504
Urban1	540	0.425	0.165	0.135	0.893
Urban2	540	0.336	0.161	0.135	0.898
Growth rates					
Income per capita	510	0.112	0.0459	-0.0376	0.261
Industrialization	510	0.00782	0.0331	-0.0898	0.171
Energy Intensity	510	-0.0373	0.0615	-0.269	0.259
Coal Intensity	510	-0.0627	0.131	-0.65	0.694
Electricity Intensity	510	-0.0132	0.0806	-0.312	0.565
Urban1	510	0.0433	0.105	-0.423	1.295
Urban2	510	0.0225	0.0465	-0.135	0.586

Source: China Statistical Yearbooks, China Population Statistical Yearbooks and China Energy Statistical Yearbooks.

Table 2.3 Annual average population summary in 30 provinces (1995-2012)

Rank of difference value	Province	Urban population at year end	Non-agricultural population	Difference value
1	Guangdong	6419	3796	2623
2	Zhejiang	3111	1281	1830
3	Shandong	4581	3209	1371
4	Henan	3442	2129	1312
5	Hunan	2718	1494	1223
6	Jiangsu	4390	3198	1192
7	Anhui	2487	1411	1076
8	Sichuan	3092	2034	1057
9	Hebei	2996	1940	1056
10	Fujian	1984	1054	931
11	Guangxi	1812	939	873
12	Yunnan	1536	728	808
13	Shanghai	1924	1143	781
14	Jiangxi	1863	1150	713
15	Beijing	1543	898	645
16	Hubei	2703	2089	614
17	Liaoning	2645	2045	599
18	Shanxi	1603	1029	575
19	Shaanxi	1609	1043	565
20	Chongqing	1455	893	563
21	Guizhou	1100	620	481
22	Tianjin	949	574	375
23	Inner Mongolia	1290	930	360
24	Heilongjiang	2107	1803	304
25	Gansu	875	617	258
26	Jilin	1456	1211	245
27	Hainan	416	291	125
28	Qinghai	237	156	81
29	Ningxia	287	212	75
30	Xinjiang	867	809	57

Source: NBSC website, http://data.stats.gov.cn/. Unit: 10,000 person. For Tibet, the urban population at year end is 650,000 and non-agricultural population is 440,000.

Table 2.4 Tests for cross-section dependence and units roots

Variable	CD-test	p-value	corr	abs(corr)	CIPS	p-value
TEI	70.79	0	0.8	0.8	-2.372	0.328
CEI	72.37	0	0.818	0.819	-1.819	0.995
EEI	21.06	0	0.238	0.52	-2.265	0.555
Income per capita	88	0	0.994	0.994	-1.815	0.995
Industrialization	32.02	0	0.362	0.64	-1.718	0.999
Urban1	80.1	0	0.905	0.905	-1.863	0.99
Urban2	79.88	0	0.903	0.903	-1.299	1
CEI in Construction Industry	33.55	0	0.379	0.55	-1.615	1
EEI in Construction Industry	19.3	0	0.218	0.429	-1.849	0.992
CEI in Transport Industry	0.23	0.82	0.003	0.369	-1.586	1
EEI in Transport Industry	72.79	0	0.832	0.823	-2.392	0.29
CEI in Tertiary Industry	6.39	0	0.072	0.437	-2.436	0.214
EEI in Tertiary Industry	11.39	0	0.129	0.499	-2.926	0
Residential Coal Intensity	14.53	0	0.164	0.369	-2.12	0.821
Residential Electricity Intensity	82.59	0	0.933	0.933	-1.635	1

Note: For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. Column 1 and 5 show the statistical values of the CD test and CIPS test while column 2 and 6 provide the corresponding p-values. Column 3 and 4 provide the average correlation and the average absolute correlation between the cross-sectional units.

Table 2.5 Determinants of TEI, CEI and EEI (Pooled OLS estimates 1995-2012)

VARIABLES	(1) OLS TEI	(2) OLS CEI	(3) OLS EEI	(4) OLS TEI	(5) OLS CEI	(6) OLS EEI
Income per capita	-1.052***	-1.517***	-0.804***	-1.136***	-1.491***	-0.803***
	(0.054)	(0.090)	(0.058)	(0.045)	(0.078)	(0.059)
Industrialization	1.923***	3.337***	1.696***	2.304***	3.517***	1.865***
	(0.185)	(0.440)	(0.184)	(0.181)	(0.444)	(0.188)
Urban1	2.011***	1.795***	1.392***			
	(0.163)	(0.294)	(0.165)			
Urban2				2.255***	1.648***	1.345***
				(0.138)	(0.242)	(0.162)
Observations	540	540	540	540	540	540
Adjusted R-squared	0.491	0.647	0.283	0.569	0.654	0.303
CD test (p value)	0.005	0.008	0.072	0.005	0.007	0.076
CIPS test (p value)	0.995	0.982	0.992	0.937	1.000	1.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Year dummies are included in each specification.

Table 2.6 Determinants of TEI, CEI and EEI (Fixed effects estimates 1995-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE	FE	FE	FE
VARIABLES	TEI	CEI	EEI	TEI	CEI	EEI
Income per capita	-0.469**	-0.400*	-0.492*	-0.421**	(0.369)	-0.435*
	(0.184)	(0.233)	(0.249)	(0.171)	(0.244)	(0.222)
Industrialization	1.325**	1.676**	1.309**	1.474**	1.731*	1.479**
	(0.507)	(0.792)	(0.513)	(0.572)	(0.886)	(0.537)
Urban1	0.919***	0.753	1.126***			
	(0.277)	(0.456)	(0.326)			
Urban2				0.875*	0.112	0.964*
				(0.447)	(0.748)	(0.497)
Observations	540	540	540	540	540	540.000
Number of provinces	30	30	30	30	30	30
Adjusted R-squared	0.782	0.795	0.403	0.767	0.790	0.353
CD test (p value)	0.004	0.013	0.069	0.004	0.011	0.059
CIPS test (p value)	0.422	0.746	0.998	0.668	0.821	0.989

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Year dummies are included in each specification.

Table 2.7 Determinants of TEI, CEI and EEI (Mean group estimates 1995-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
	MG	MG	MG	MG	MG	MG
Dependent variables	TEI	CEI	EEI	TEI	CEI	EEI
Income per capita	-0.493***	-0.772***	-0.298***	-0.542***	-0.824***	-0.291***
	(0.072)	(0.136)	(0.071)	(0.065)	(0.130)	(0.067)
Industrialization	1.399***	2.364***	1.005***	1.397***	2.891***	0.406
	(0.252)	(0.691)	(0.316)	(0.279)	(0.782)	(0.312)
Urban1	0.207	(0.237)	0.761**			
	(0.344)	(0.571)	(0.300)			
Urban2				2.211**	1.368	1.286**
				(0.981)	(1.280)	(0.591)
Observations	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30
RMSE	0.055	0.119	0.063	0.059	0.133	0.066
CD test (p value)	0.000	0.000	0.000	0.000	0.000	0.000
CIPS test (p value)	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Table 2.8 Determinants of TEI, CEI and EEI (Augmented mean group estimates 1995-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
	AMG	AMG	AMG	AMG	AMG	AMG
Dependent variables	TEI	CEI	EEI	TEI	CEI	EEI
Income per capita	-0.662***	-0.287**	-0.690***	-0.630***	(0.162)	-0.809***
	(0.054)	(0.136)	(0.090)	(0.047)	(0.186)	(0.098)
Industrialization	0.632**	0.902	0.510*	0.452	0.755	0.379
	(0.247)	(0.607)	(0.283)	(0.296)	(0.649)	(0.288)
Urban1	0.496	1.473**	0.753**			
	(0.377)	(0.730)	(0.319)			
Urban2				1.024**	1.272	0.256
				(0.503)	(1.580)	(0.607)
Observations	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30
RMSE	0.037	0.097	0.056	0.039	0.099	0.058
CD test (p value)	0.046	0.144	0.063	0.181	0.058	0.046
CIPS test (p value)	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Table 2.9 Mean group estimation on channel one “Construction” (Heterogeneous estimates 1995-2012)

VARIABLES	(1) MG CEI	(2) AMG CEI	(3) MG EEI	(4) AMG EEI	(5) MG CEI	(6) AMG CEI	(7) MG EEI	(8) AMG EEI
Income per capita	-0.549***	-0.119	-0.288***	-0.790***	-0.617***	-0.085	-0.275***	-0.691***
	(0.180)	(0.134)	(0.084)	(0.092)	(0.150)	(0.183)	(0.057)	(0.108)
Industrialization	2.068***	0.809*	0.378	0.294	2.517***	0.905	0.029	-0.119
	(0.645)	(0.432)	(0.343)	(0.309)	(0.723)	(0.558)	(0.328)	(0.271)
EI in construction sector	0.479***	0.285**	0.253*	0.323***	1.123***	0.650**	0.372*	0.605*
	(0.135)	(0.121)	(0.146)	(0.123)	(0.397)	(0.314)	(0.204)	(0.356)
Urban1	-2.169	0.055	-1.196	-2.439**				
	(2.118)	(1.236)	(1.601)	(1.167)				
Urban1 * EI in construction sector	-1.135***	-0.520*	-0.640	-0.831***				
	(0.396)	(0.315)	(0.433)	(0.320)				
Urban2					-11.143**	-5.766	-0.442	-5.945
					(4.852)	(4.021)	(2.015)	(5.417)
Urban2 * EI in construction sector					-3.809***	-1.842*	-1.205**	-2.234**
					(1.213)	(1.105)	(0.568)	(1.071)
Observations	540	540	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30	30	30
RMSE	0.099	0.085	0.047	0.041	0.098	0.071	0.049	0.042
CD test (p value)	0.000	0.474	0.000	0.468	0.000	0.095	0.000	0.469
CIPS test (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Table 2.10 Mean group estimation on channel two “Transport” (Heterogeneous estimates 1995-2012)

VARIABLES	(1) MG CEI	(2) AMG CEI	(3) MG EEI	(4) AMG EEI	(5) MG CEI	(6) AMG CEI	(7) MG EEI	(8) AMG EEI
Income per capita	-0.739***	-0.408***	-0.422***	-0.712***	-0.788***	-0.094	-0.422***	-0.796***
	(0.132)	(0.121)	(0.077)	(0.078)	(0.132)	(0.184)	(0.081)	(0.070)
Industrialization	1.921***	1.032**	1.221***	0.303	2.349***	0.99	0.726*	0.21
	(0.703)	(0.448)	(0.291)	(0.338)	(0.799)	(0.623)	(0.384)	(0.371)
EI in transport sector	0.205	0.277	0.034	0.323***	0.629*	0.501*	-0.149	0.341**
	(0.257)	(0.186)	(0.082)	(0.076)	(0.374)	(0.290)	(0.199)	(0.168)
Urban1	-0.342	-0.897	1.654	-2.273				
	(3.219)	(2.537)	(1.158)	(1.450)				
Urban1 * EI in transport sector	-0.161	-0.514	0.064	-0.589**				
	(0.561)	(0.428)	(0.170)	(0.231)				
Urban2					-9.958*	-12.900**	5.037	-2.847
					(5.885)	(5.970)	(3.657)	(3.484)
Urban2 * EI in transport sector					-1.923	-1.930**	0.395	-0.738
					(1.201)	(0.937)	(0.682)	(0.663)
Observations	540	540	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30	30	30
RMSE	0.089	0.076	0.042	0.034	0.098	0.074	0.044	0.037
CD test (p value)	0.040	0.198	0.000	0.071	0.000	0.066	0.000	0.033
CIPS test (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Table 2.11 Mean group estimation on channel three "Wholesale" (Heterogeneous estimates 1995-2012)

VARIABLES	(1) MG CEI	(2) AMG CEI	(3) MG EEI	(4) AMG EEI	(5) MG CEI	(6) AMG CEI	(7) MG EEI	(8) AMG EEI
Income per capita	-0.686***	-0.343***	-0.269***	-0.632***	-0.622***	-0.402***	-0.277***	-0.585***
	(0.117)	(0.114)	(0.079)	(0.070)	(0.151)	(0.145)	(0.061)	(0.067)
Industrialization	2.042***	0.804**	0.563*	0.071	2.370***	1.221***	-0.05	-0.305
	(0.607)	(0.344)	(0.334)	(0.341)	(0.678)	(0.322)	(0.293)	(0.264)
EI in tertiary sector	0.510***	0.332**	0.031	-0.003	0.974**	0.312	-0.397	0.177
	(0.164)	(0.156)	(0.160)	(0.129)	(0.477)	(0.318)	(0.416)	(0.275)
Urban1	-2.293	-1.565	2.914***	1.819				
	(1.611)	(1.446)	(1.071)	(1.262)				
Urban1 * EI in tertiary sector	-1.001***	-0.633*	0.413	0.194				
	(0.385)	(0.381)	(0.384)	(0.489)				
Urban2					-5.51	-4.199	6.824	2.412
					(4.076)	(3.527)	(5.324)	(4.742)
Urban2 * EI in tertiary sector					-2.595*	-1.073	1.374	-0.122
					(1.548)	(1.053)	(1.416)	(1.193)
Observations	540	540	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30	30	30
RMSE	0.083	0.074	0.045	0.038	0.090	0.074	0.048	0.041
CD test (p value)	0.119	0.316	0.000	0.046	0.000	0.254	0.000	0.206
CIPS test (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

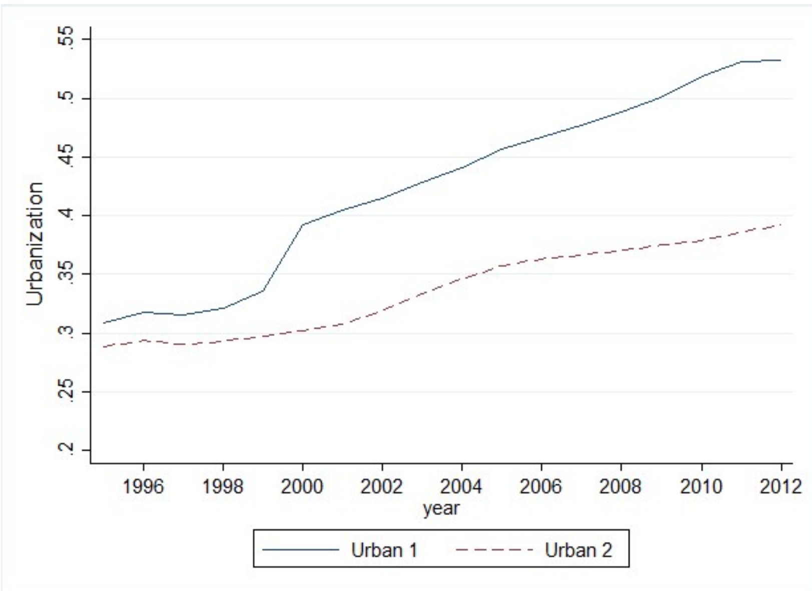
Table 2.12 Mean group estimation on channel four “Residential” (Heterogeneous estimates 1995-2012)

VARIABLES	(1) MG CEI	(2) AMG CEI	(3) MG EEI	(4) AMG EEI	(5) MG CEI	(6) AMG CEI	(7) MG EEI	(8) AMG EEI
Income per capita	-0.688***	-0.503***	-0.501***	-0.822***	-0.662***	-0.399**	-0.592***	-0.847***
	(0.122)	(0.088)	(0.086)	(0.081)	(0.114)	(0.169)	(0.092)	(0.086)
Industrialization	1.591***	0.684	1.116***	0.505*	2.102***	1.178*	0.781**	0.491
	(0.609)	(0.578)	(0.346)	(0.273)	(0.633)	(0.657)	(0.398)	(0.367)
Residential EI	0.960***	0.405*	0.156**	0.260***	2.103***	0.898*	-0.094	0.256
	(0.197)	(0.233)	(0.069)	(0.053)	(0.589)	(0.482)	(0.219)	(0.171)
Urban1	-5.017***	-2.314	0.881	0.11				
	(1.896)	(1.464)	(0.811)	(0.944)				
Urban1 * Residential EI	-2.107***	-0.785	0.113	0.01				
	(0.563)	(0.585)	(0.180)	(0.232)				
Urban2					-17.298***	-9.239*	9.587**	2.67
					(5.212)	(5.121)	(3.928)	(2.775)
Urban2 * Residential EI					-5.593***	-2.322	1.460*	0.18
					(1.687)	(1.451)	(0.870)	(0.705)
Observations	540	540	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30	30	30
RMSE	0.089	0.081	0.039	0.030	0.091	0.079	0.038	0.031
CD test (p value)	0.000	0.389	0.000	0.363	0.000	0.154	0.000	0.118
CIPS test (p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

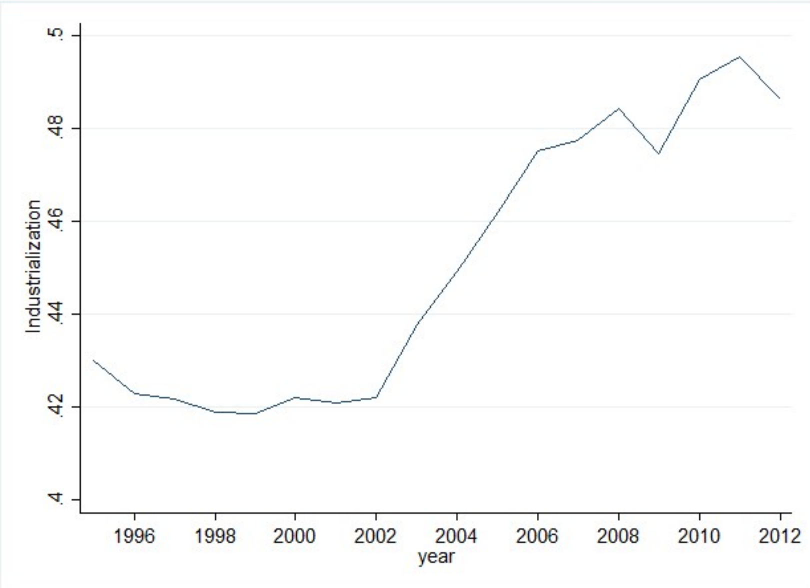
Appendix A

Fig. A.1 Chinese Annual Average Urbanization in 30 Provinces (1995-2012)



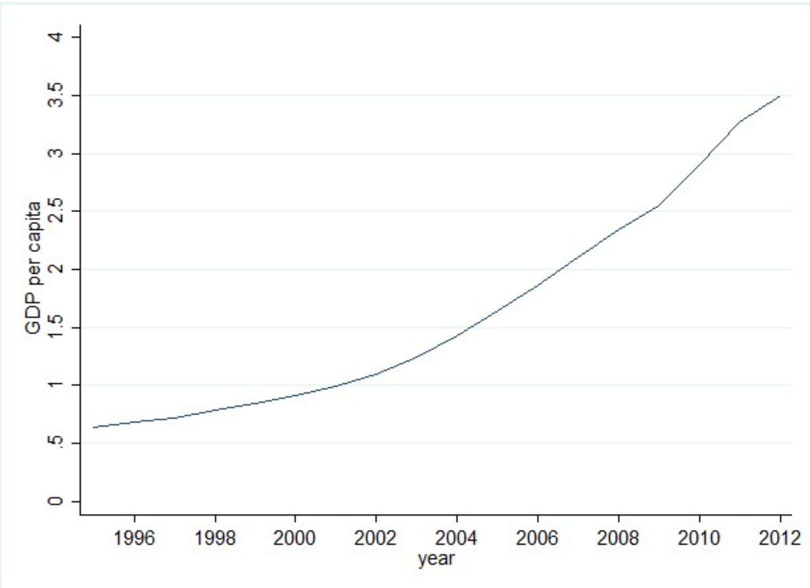
Source: China Statistical Yearbooks and China Population Statistical Yearbooks 1996-2013

Fig. A.2 Chinese Annual Average Industrialization in 30 Provinces (1995-2012)



Source: China Statistical Yearbooks 1996-2013 (Units: Secondary industry added value/GDP)

Fig. A.3 Chinese Annual Average Income per capita in 30 Provinces (1995-2012)



Source: China Statistical Yearbooks 1996-2013 (Units: 10,000 RMB/person in 2005 prices)

Table A.1 Variables explanations

Variables	Meaning	Units
Total Energy Intensity (TEI)	Total energy consumption/Real GDP	Tons standard coal/10,000 RMB
Coal Intensity (CEI)	Coal consumption/Real GDP	10,000 tons/10,000 RMB
Electricity Intensity (EEI)	Electricity consumption/Real GDP	100 million kWh
Income per capita	Real GDP/Total population at year end	10,000 RMB/person
Industrialization	Industrial value added/GDP	
Urban1	Urban population at year end/Total population at year end	
Urban2	Non-agricultural population/Total registered population	
Coal Intensity in Construction Industry	Coal consumption in construction industry/Real value added in construction industry	10,000 tons/10,000 RMB
Electricity Intensity in Construction Industry	Electricity consumption in construction industry/Real value added in construction industry	kWh/yuan
Coal Intensity in Transport Industry	Coal consumption in transport, storage and post industry/ Total population at year end	Tons/person
Electricity Intensity in Transport Industry	Electricity consumption in transport, storage and post industry/ Total population at year end	10,000 kWh/person
Coal Intensity in Tertiary Industry	Coal consumption in wholesale, retail trade and hotel, restaurants industry/Real value added in wholesale, retail trade and hotel, restaurants industry	10,000 tons/10,000 RMB
Electricity Intensity in Tertiary Industry	Electricity consumption in wholesale, retail trade and hotel, restaurants industry/ Real value added in wholesale, retail trade and hotel, restaurants industry	kWh/yuan
Residential Coal Intensity	Residential coal consumption/Total population at year end	Tons/person
Residential Electricity Intensity	Residential electricity consumption/Total population at year end	10,000 kWh/person

Source: China Statistical Yearbooks, China Population Statistical Yearbooks and China Energy Statistical Yearbooks for various years on China Data Online.

Table A.2 Correlation matrix for primary variables

	Total energy intensity	Income per capita	Industrialization	Urban1	Urban2
Total energy intensity	1				
Income per capita	-0.606	1			
Industrialization	-0.508	0.613	1		
Urban1	-0.449	0.847	0.365	1	
Urban2	-0.296	0.696	0.218	0.895	1

Note: Total energy intensity and income per capital are in natural logs. Observations N=540.

Table A.3 Determinants of TEI, CEI and EEI (CCEMG 1995-2012)

VARIABLES	(1) CCEMG TEI	(2) CCEMG CEI	(3) CCEMG EEI	(4) CCEMG TEI	(5) CCEMG CEI	(6) CCEMG EEI
Income per capita	0.405***	0.529*	0.192	0.100	0.349	0.140
	(0.111)	(0.271)	(0.133)	(0.115)	(0.237)	(0.156)
Industrialization	0.176	0.776	0.538	0.567*	-0.259	0.191
	(0.231)	(0.540)	(0.397)	(0.326)	(0.937)	(0.506)
Urban1	0.869**	0.599	0.444			
	(0.394)	(0.841)	(0.356)			
Urban2				0.469	1.753	0.886
				(0.565)	(1.363)	(0.542)
Observations	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30
RMSE	0.0285	0.0781	0.0432	0.0315	0.0695	0.0393
CD test (p value)	0.0627	0.105	0.0438	0.0471	0.0552	0.0748
CIPS test (p value)	0	0	0	0	0	0

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Table A.4 Common correlated effects mean group estimation on four channels (Heterogeneous estimates 1995-2012)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Construction				Transport				Wholesale				Residential			
VARIABLES	CEI	EEI	CEI	EEI	CEI	EEI	CEI	EEI	CEI	EEI	CEI	EEI	CEI	EEI	CEI	EEI
Income per capita	0.415	-0.024	0.437	0.070	0.559	0.132	0.249	0.229	0.277	0.026	-0.082	0.002	0.340	0.048	0.171	0.321***
	(0.427)	(0.226)	(0.432)	(0.176)	(0.341)	(0.161)	(0.226)	(0.166)	(0.315)	(0.218)	(0.307)	(0.184)	(0.302)	(0.151)	(0.348)	(0.103)
Industrialization	0.844	-0.143	1.765	0.405	0.379	-0.035	0.034	0.210	0.966	-0.063	0.435	-0.163	1.657***	0.061	1.102	-0.033
	(0.753)	(0.467)	(1.088)	(0.490)	(0.734)	(0.482)	(1.054)	(0.561)	(0.694)	(0.401)	(0.817)	(0.417)	(0.541)	(0.432)	(0.776)	(0.504)
Channel-specific EI	0.027	0.262**	0.399	0.233	0.245	0.156	0.906***	-0.069	0.015	0.093	-0.678*	-0.263	0.321	-0.095	1.292*	-0.086
	(0.129)	(0.123)	(0.495)	(0.195)	(0.181)	(0.104)	(0.328)	(0.197)	(0.150)	(0.154)	(0.389)	(0.304)	(0.366)	(0.210)	(0.667)	(0.188)
Urban 1	0.443	-0.289			1.423	1.050			-1.193	0.767			3.652	-2.527		
	(1.511)	(0.742)			(1.562)	(0.876)			(1.957)	(1.038)			(4.944)	(1.905)		
Urban 1 * EI	-0.012	-0.773**			-0.253	-0.192			0.481	-0.034			-0.179	0.461		
	(0.423)	(0.332)			(0.465)	(0.249)			(0.398)	(0.380)			(0.849)	(0.523)		
Urban 2			-1.145	1.000			10.511*	-0.273			-5.770	1.692			24.859*	-2.277
			(5.665)	(1.016)			(6.077)	(1.793)			(3.990)	(3.020)			(12.842)	(1.975)
Urban 2 * EI			-0.934	-0.218			-2.473***	0.631			1.867*	0.872			-4.231*	0.906
			(1.863)	(0.600)			(0.863)	(0.682)			(1.071)	(0.802)			(2.304)	(0.599)
Observations	540	540	540	540	540	540	540	540	540	540	540	540	540	540	540	540
Number of provinces	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
RMSE	0.0622	0.0249	0.0489	0.0260	0.0463	0.0213	0.0451	0.0191	0.0439	0.0239	0.0421	0.0229	0.0585	0.0195	0.0462	0.0196
CD test (p value)	0.918	0.643	0.0474	0.687	0.201	0.203	0.158	0.0363	0.246	0.0573	0.0441	0.904	0.172	0.298	0.145	0.983
CIPS test(p value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Estimation is based on a balanced panel of 30 provinces 1995 to 2012. P values are reported for the CD and CIPS tests. For the CD test, the null hypothesis is cross sectional independence. For the CIPS test, the null hypothesis is non-stationarity. RMSE (root mean square error). Robust standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% levels respectively.

Chapter 3

Electricity Prices and Industry Switching: Evidence from Chinese Manufacturing Firms

Statement of Authorship

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Principal Author

Name of Principal Author (Candidate)	Tong Zhu		
Contribution to the Paper	Collected and cleaned the data, performed the econometric and statistical analysis and prepared the manuscript		
Overall percentage (%)	85%		
Signature	Tong Zhu	Date	08/09/2017

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Robert Elliott		
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Electricity Prices and Industry Switching: Evidence from Chinese Manufacturing Firms

Abstract

Energy is an essential input into a firm's production process. Understanding how firms respond to changes in energy prices is important for understanding the micro-foundations of growth in developing economics. In this paper we investigate how electricity price changes affect firms' production choices in China during the period 2005 and 2007. Employing an instrumental approach to address potential endogeneity concerns, our results show that the energy price plays an important role in shifting industrial production towards industries with lower energy intensities. More specifically, we find that manufacturing firms are more likely to switch to less energy intensive industries as a result of rising cost of energy. A 10% electricity price increase leads to an increase in the probability of switching to a less energy intensive industry by approximately 2.34% to 2.42%. Our results imply that electricity prices can be an effective way to promote energy efficiency through resource reallocation between industries.

JEL: L6; O13; O14

Keywords: Sector switching; Electricity prices; Firm behaviour

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3.1 Introduction

Energy is a fundamental input for manufacturing production and energy costs account for a significant part of operational costs. Electricity costs as a percentage of total production costs or value added for energy intensive sectors range from a low of 12-16% for blast/basic oxygen furnace steel production and textiles, to 20-25% for electric arc furnace steel and copper, to 30-50% for aluminum and chemicals (BLS and Tractus, 2016). Since firms are an important engine of growth in the economy and energy is an essential input in the production process, identifying how firms respond to energy supply shocks is crucial for understanding the growth in developing economies.

In this paper we investigate how changes in energy prices affect firm behaviour in different provinces for the period 2005 to 2007. Specifically, we test the impact of input constraints on firm's choice of industry under the exogenous electricity prices. Employing an instrumental approach, our results suggest that higher electricity prices tend to promote surviving firms to adjust the 4-digit industry they operate in. In particular, we find that higher energy costs provide an incentive for firms to switch to a less energy intensive industry, and dampen a firm's desire to switch to a more energy intensive industry. With our preferred method a 10% electricity price increase leads to a 2.34% to 2.42% increase in the probability of a firm switching to a less energy intensive industry, and a 2.12% to 2.24% drop in the probability of a firm switching to a more energy intensive industry all else being equal. The dampening effect also depends on a firm's initial energy intensity level. Energy prices are shown to be an efficient tool in promoting industrial structure shifting to less energy intensive one and bolstering energy efficiency. Besides energy costs, we also find some significant firm-level characteristics and industrial characteristics that influence firms' switching decision. For example, switchers tend to be large-size highly productive firms relative to the average, and state-owned firms are generally less likely to switch their main products. Furthermore, our findings confirmed the interest conflict between the central and local authorities in terms of the electricity pricing regime.

The contribution of this paper is two-fold. First, this is the first paper to study how varying electricity prices in China affect the industry choice of firms. Our approach is to combine a unique regional industrial electricity price dataset with a comprehensive firm-level dataset. Understanding the impact of electricity costs on firms' industry choices and hence technology choices is important due to the implications for a country's industrial structure and subsequent economic growth potential. The industrial electricity price dataset comes from National Development and Reform Commission (NDRC) and covers 36 large and medium sized cities in China. The firm-level dataset is the Chinese Industrial Enterprises Dataset which includes all state-owned enterprises and private enterprises with more than 5 million RMB yearly turnover.

Second, we construct an instrumental variable from the interaction of regional coal production and thermal power generation capacity to isolate the exogenous variation in energy prices. Recently, there has been a growing interest in investigating the impact of energy prices on firms behaviour. However, most of these studies have ignored the endogeneity issue of the energy price. The electricity price scheme in China is originally designed in the 1960s and developed in the 1980s under which there are several categories of end users. Each type of end user is assigned a specific price by provincial and local pricing bureaus under the guidance of the central government. Hence, the endogeneity concerns may arise from the political influence under which the low energy prices serve as a favourable policy used by local officials to support industries in their jurisdictions. Unobserved political influence might impact both local energy prices and firm performance. Employing instruments which affect firm behaviour only through the price variation help us to obtain more precise estimation results.

The reminder of the paper is organized as follow. Section 3.2 provides a summary of the literature on firm performance under energy constrains and the switching behaviour. Section 3.3 and 3.4 describe the methodology and statistical description of the data. The empirical results are presented in Section 3.5 and the final section concludes and discusses the policy implications.

3.2 Literature Review

The literature that examines the impact of energy related costs on firm performance has received renewed attention in recent years. Energy related costs appeared in the literature can take different forms such as power shortages, electricity prices and production costs of energy. Indicators used to measure firm performance include output, productivity, profitability, employment and investment. Existing research recognises the critical role played by energy prices in affecting manufacturers' productivity and output. However, there has been little discussion about the price impact on existing firms' product choice. Furthermore, empirical evidence has shown that incumbent firms that switch into new industries tend to behave differently compared with newly created firms. In this section we document the literature on the effect of energy related costs and the literature on the switching behaviour.

Due to the importance of a reliable power supply for industrial production, one group of studies focuses on the impact of power shortages on firm performance especially in developing countries (Hallward-Driemeier and Stewart, 2004; Dollar et al., 2005; Alby et al., 2012; Alam, 2013; Allcott et al., 2016; Fisher-Vanden et al., 2015). By investigating the quality of infrastructure, Hallward-Driemeier and Stewart (2004) find that a large number of firms in poor countries have suffered from erratic and low quality power supply, which is estimated to have reduced sales by up to 10%. Based on survey data from Bangladesh, China, India and Pakistan, Dollar et al. (2005) demonstrate that the reliability of the public power grid is an important determinant in firm performance and power outages are one of the most serious barriers to firms increasing productivity and profitability. From a global perspective, Alby et al. (2012) develop a theoretical framework to explain the investment behaviour of enterprises under physical constraints. Using data from 87 countries covering 28 two-digit ISIC industrial classification, their empirical results reveal that power outages have a non-linear effect on investment capacity and the corresponding industrial structure across countries and sectors. The non-linear effect varies according to the degree of power dependency as well as firm size.

At the country level, Alam (2013) and Allcott et al. (2016) consider the Indian electricity supply as an example and Fisher-Vanden et al. (2015) focus on China. Alam (2013) studies Indian firms' adaptation to electricity outages and states that outages may not necessarily lead to output reductions due to the adjustment in production process and input demand. The impact of electricity shortages on firms is heterogeneous with firms operating in electricity-intensive industries expected to be the major losers. Instrumenting electricity shortages with supply shifts from hydroelectric power availability, Allcott et al. (2016) find that power shortages for Indian manufacturing lead to an average decline in revenues and producer surplus of approximately 5 to 10 percent with relatively small losses in productivity due to input adjustments. Similar conclusions have been found for China. Fisher-Vanden et al. (2015) study the severe electricity shortages due to the repaid growth of electricity demand in the early 2000s and the resulting influence on Chinese firms. Production costs are found to rise by 8% due primarily to the increase in outsourcing of intermediate inputs.

Other studies have estimated the impact of electricity from the perspective of price variation rather than shortages (Davis et al., 2008, 2013; Dilaver and Hunt, 2011; Abeberese, 2012; Ganapati et al., 2016). Although a negative relationship is observed between the electricity price and electricity productivity, Davis et al. (2008) predict a positive price elasticity on plant-level output per kWh equal to 0.6 for period from 1985 to 2000.[1] The result implies a long-run improvement in energy efficiency caused by higher prices for U.S manufacturing. They also found a tradeoff between electricity productivity and labour productivity since large plants facing lower energy costs have a reduced incentive to invest in physical capital. Price dispersion faced by U.S. plants located in various states has been further documented by Davis et al. (2013). Around 85-95% of the differential can be explained by regional factors, such as generation costs and regulatory factors across states, and purchase quantity. Utilizing the structural series technique, Dilaver and Hunt (2011) found a electricity price elasticity of -0.16 for Turkish industrial electricity consumption over the period 1960 to 2008. Abeberese (2012) examines the electricity price effect on a series of Indian firm outcomes including industry choice, product mix, capital-labour ratio and productivity. The main finding is that a 1% increase in electricity price instrumented by generation conditions lead to approximately 1.6 to 1.8 percentage point change in the probability of a firm switching industries. Output, the capital labour ratio and labour productivity are also shown to decrease as a result of an increasing electricity price. A recent study of Ganapati et al. (2016) develops a partial equilibrium methodology to estimate how the energy price change is shared between U.S. manufacturers and consumers. They find that under the imperfect market competition environment, costumers bear about 70 percent of energy price-driven changes in input costs.

In terms of firms' switching behaviour, evidence has been found by several studies investigating the multi-production and firm turnover(Redding et al., 2006; Bernard et al., 2006, 2007; Goldberg et al., 2010; Newman et al., 2013). Redding et al. (2006) is one of the most important studies that investigates product switching of surviving firms. Using the quinquennial U.S. Manufacturing Censuses data from 1972 to 1997, they find that product

[1] In the study regional fixed effects as well as power generation shares from hydro, nuclear and petrol/natural gas are employed as instruments for the electricity price per kWh paid by plants to isolate the exogenous variation.

switching is frequent and prevalent among U.S. firms. Approximately two-thirds of firms have altered their mix of five-digit SIC products every five years and the change in output due to the adding and dropping of products by surviving firms accounts for approximately one-third of the aggregate change.[2]

Determinants of product switching include demand and supply shocks which are product-specific but common to all firms. Under this scenario the adding and dropping rates for the same product tend to be negatively correlated since popular products should be added by more firms and dropped by fewer firms and vice versa. A complementary explanation of switching is derived from an extended industrial dynamic model, where the interaction between firms and products is emphasized and where sunk costs play a fundamental role in determining product-market entry or exit. Generally speaking the findings suggest that product switching leads to a more efficient resource allocation within firms and makes a notable contribution to firm and aggregate growth. One type of supply shock, namely trade liberation, has been further investigated by Bernard et al. (2006) and shows that switching rates tend to increase with trade liberalization. As trade costs fall, firms' product scope shrinks and the least- productive product tends to be dropped by surviving exporters. When focusing on trade exposure to low-wage countries, the capital-labour ratio plays an important role in determining firms' switching behavior since labour-intensive firms are more susceptible to import from low-wage countries due to the comparative advantage (Bernard et al., 2007).

According to Goldberg et al. (2010), compared to US firms, product switching is far less common in large developing countries such as India. Although multi-product firms account for 47% of manufacturing firms over a 5 year period only 28% of firms report a product switch compared to a 54 percent for US firms. However, common features for both India and US firms include that large and multi-product firms tend to be more likely to engage

[2] Product switching in Redding et al. (2006)'s study is defined at 5-digit SIC level which consists of 1,848 products in total.

in switching behavior. Looking at Vietnamese data at the firm, sector and industry levels, Newman et al. (2013) demonstrate that switchers have different characteristics and behave differently to newly established firms and exiting firms. Large firms with higher productivity involved in multi-product production tend to have a higher probability of switching into a new sector, while small firms with single products are more likely to switch out. There is also weak evidence that firm characteristics such as the capital-labour ratio and ownership play only a minor role in promoting switching.

3.3 Empirical Strategy

3.3.1 Dependent variables

Following Newman et al. (2013), we define the switching behaviour as a firm whose main product in year t and main product in year $t+1$ are from different four-digit industries[3]. Table 3.1 provides an illustrative example for the switching behaviour. A dummy variable $Switch$ is defined as missing for all switchers since the year after switching. By doing so we exclude the disturbance from industry switches in when we consider the characteristics of the original industry.

[Table 3.1 about here]

This study aims to analyze the impact of energy prices on a firm's switching decision. Our priors are that firms located in provinces with high energy prices will have a higher probability of switching into less energy intensive industries compared to firms located in low energy cost provinces everything else equal. To measure whether a firm switches from high to low or low to high energy intensity (hereafter, EI) industries, ideally we would have the 4-digit level

[3]The 4-digit industry classification that we use in this paper is GB/T4754-2002.

energy consumption information. However, unfortunately such information is unavailable for Chinese manufacturing industries. Our solution is to consider energy inputs and fixed capital as complements. The correlation between 2-digit electricity consumption and 2-digit fixed capital is 0.845 during our study period. Hence, we decompose the industrial electricity consumption at the 2-digit level to create an estimate of electricity inputs at the 4-digit level using the proxy of total fixed capital.[4] Equation 3.1 is now calculated using sectoral electricity consumption disaggregated into industrial electricity consumption.

$$\frac{FA_{4-digit,t}}{FA_{2-digit,t}} = \frac{EC_{4-digit,t}}{EC_{2-digit,t}}$$

$$EC_{4-digit,t} = \frac{FA_{4-digit,t}}{FA_{2-digit,t}} \times EC_{2-digit,t} \tag{3.1}$$

FA and *EC* represent the total fixed capital aggregated from firm-level data and electricity consumption respectively.

For our measure of electricity consumption at the 4-digit level, energy intensity at the 4-digit level is then defined as electricity consumption at the 4-digit level over total industrial output aggregated from firm-level data.

$$EI_{4-digit,t} = \frac{EC_{4-digit,t}}{Y_{4-digit,t}} = \frac{FA_{4-digit,t} \times EC_{2-digit,t}}{FA_{2-digit,t} \times Y_{4-digit,t}} \tag{3.2}$$

From our 4-digit energy intensity estimates, we can now identify the direction of switching behaviour. A dummy variable *Switch_HL* is used to mark the switching behaviour from a high EI industry to a low EI industry; *Switch_LH* signals switching the other way around. Furthermore, we define the extent of the change in EI (or EI gap) as the absolute value of the

[4]The relationship of complementarity between energy and fixed capital has been analyzed extensively by previous researchers. For example, the E-K complementarity is found for manufacturing sectors in U.S. (Berndt and Wood, 1979), Canada (Fuss, 1977), Netherlands (Magnus, 1979), UK (Hunt, 1984) and New Zealand (Patterson, 1996). Recent studies include Apergis and Payne (2009) Mazzanti and Zoboli (2009) Pablo-Romero and Sánchez-Braza (2015), and Khayyat (2015) for a detailed literature review.

EI difference between the current industry and the industry that a firm switches into. Hence, for switchers, the *EI gap* is given by

$$EI\ gap_{ispt} = |EI_{isp,t} - EI_{isp,t+1}| \tag{3.3}$$

For non-switchers, *EI gap* is

$$EI\ gap_{ispt} = 0 \tag{3.4}$$

The dependent variable *EI gap* quantifies how large the energy intensity difference is between the current industry and the next industry. This can be considered as a measure of the difficulty a firm faces when switching its main product from the perspective of energy inputs.

3.3.2 Independent variables

Our main variable of interest is the energy price. We measure local industrial electricity prices (*IEP*) at the province level. Due to data limitations, the time period for our industrial electricity price dataset is relatively short and only covers the years 2005 to 2007. Hence, other regional impact factors are assumed to be time invariant and proxied by province specific dummies.

Since firms evaluate their decisions and adjust future expectations on the basis of current production and capabilities (Newman et al., 2013), productivity plays a crucial role in the decision making process of the firm. We employ two variables to represent the firm productivity level, namely total factor productivity (*TFP*) using the LP method (Levinsohn and Petrin, 2003) and the value added per worker (*Labor productivity*). We also include total fixed assets per worker (*KL ratio*) as a measure of sunk costs of production. In a study of US manufacturing firms from 1977 to 1997, Redding et al. (2006) find that within industries, labour intensive plants are more likely to be affected by international trade exposure and hence switch production relative to capital intensive plants. Based on the Vietnam manufacturing data, Newman et al. (2013) argue that the capital labour ratio plays a positive and significant role for new firms making the entry decision, while it is neutral or even obstructive for the decision to switch for incumbent firms.

Firm size and ownership structure are also considered important factors that may influence a firm's switching decision. Numerous studies have investigated the link between firm size (*Size*) and growth (e.g. Griliches and Mairesse, 1991; Hall, 1986; Blonigen and Tomlin, 2001) and most find a negative impact of firm size on productivity growth. Newman et al. (2013) point out that large firms may find it difficult to retrain workers if they plan to switch their industry of production. Based on U.S. manufacturing firms, Redding et al. (2006) argue that young firms with small scale production have a higher tendency to drop products. As for ownership structure, state owned firms are often considered to be less efficient and less productive than private firms as the production decisions may be politically driven (Groves et al., 1994; Jefferson and Rawski, 1994). In contrast, firms with significant foreign investment are expected to have a better performance since foreign investment from more advanced countries may allow advanced technologies as knowledge (Dunning, 1988; Carr et al., 2001; Hu et al., 2005). Using the Chinese Industrial Census data, Li et al. (2001) suggests that domestic firms benefit from the presence of foreign investment but also from competition between foreign and local firms. To control for the influence of ownership structure, we include the state-own capital share (SOE) and the share that is from foreign, Hong Kong, Macao and Taiwan owners (FIE). As a robustness check, we also use ownership dummies that are equal to one when the share of ownership exceeds 51%.

We also control for multi-product firms ($MULTI$), exports as a share of output (EXP) and investment in research and development as a share of output (*R&D*). Multi-product firms are able to reallocate resources more efficiently than their single-product competitors (Redding et al., 2006). In contrast, Goldberg et al. (2010) find that product churning is far less frequent in developing countries such as India due in part to complex industrial regulations. Hence, we separate single-product firms from multi-product firms. Bernard et al. (2006) indicates that trade liberalization can enhance firms' performance in terms of output per product and the total number of products since surviving firms reallocate resources and drop their less productive products as trade costs fall. Moreover, if firms export, they tend to export a series of goods to multiple destinations, and hence, the U.S. export market is occupied by a relatively small number of firms (Bernard et al., 2007). On the other hand, Arnold and Hussinger (2005) argue that the causal linkage from exporting to productivity growth is not always straight forward. Using German manufacturing firm data they find there is evidence of self-selection where high productive firms choose to export. As for R&D expenses, evidence shows that the induced technology transfer and innovation by R&D improve firms' productivity and expand their production scale (Griffith et al., 2004; Minniti, 2006). Firms with higher innovative capability could switch the production or produce more varieties to adapt with customers' preference and have a better chance of survival (Abernathy and Utterback, 1978; Utterback and Abernathy, 1975). As a robustness check we also use export and R&D dummies that are equal to one if export or R&D expenditure is positive.

In addition to firm characteristics we also control for industry level controls that may affect a firm's switching decision. Our industrial controls are aggregated from firm-level estimates of productivity, capital labour ratio, firm size, ownership structure, exports and R&D expenditure. We also control for the firm concentration ratio (CR) and industrial energy intensity (EI) to account for the degree of competition and the dependency on energy of an industry respectively. The existing literature that studies the effect of market concentration on firm survival tends to be inconclusive. For example, Audretsch (1991) found a positive impact of market concentration on the short-run survival rates at the industry level and no impact on the long-run scenario using U.S. manufacturing firms established in 1976. In contrast, Audretsch and Mahmood (1995) find limited evidence in a study of firm survival at the establishment level and found a negative impact of market concentration.[5]

3.3.3 Model specifications

By including a range of firm-level and industry-level characteristics that may determine whether a firm decides to switch from one 4-digit industry to another, our empirical specification is given by:

$$\begin{aligned} Pr(Switch_{ispt}) =& \alpha + \beta_1 IEP_{pt} + \beta_2 IEP_{pt} \times EI_{st} + \Phi + \Phi^{'} \\ & + \theta_s + \delta_p + \eta_t + \varepsilon_{ispt} \end{aligned} \tag{3.5}$$

$$\Phi = f\begin{pmatrix} Productivity_{ispt}, KL\ ratio_{ispt}, Size_{ispt}, SOE_{ispt} \\ FIE_{ispt}, EXP_{ispt}, R\&D_{ispt}, MULTI_{ispt} \end{pmatrix} \tag{3.6}$$

$$\Phi^{'} = f\begin{pmatrix} Productivity^N_{st}, KL\ ratio^N_{st}, Size^N_{st}, SOE^N_{st} \\ FIE^N_{st}, EXP^N_{st}, R\&D^N_{st}, CR_{st}, EI_{st} \end{pmatrix} \tag{3.7}$$

The subscripts i, s, p, t represent firm, 4-digit industry, province and year respectively. Fixed effects at the industry, province and year are given by θ_s, δ_p, η_t respectively. Firms located in provinces with costly electricity are expected to be more likely to reallocate resources and hence adjust their main goods of producing. Industries that are highly dependent on energy resources are expected to be more sensitive to energy price changes. The impact of energy prices is captured by the coefficient of IEP_{pt} as well as the coefficient of the interaction term between IEP_{pt} and EI_{st}.

[5] For more literature on market concentration, see Mata and Portugal (2002) and Geroski et al. (2010).

The industry-level variables with superscript N capture the characteristics of industry s that the firm switches out of. The industrial characteristics are calculated independently for each firm i by excluding firm i's information.[6] CR_{st} and EI_{st} are simple averages at the 4-digit industry level.

As discussed in the previous section, a potential concern is that the electricity price may be endogenous due to two possible reasons. First, firms located in regions with relatively high energy costs may make lower profits and hence, have incentives to move to different sectors in order to enjoy preferential electricity prices. The electricity price faced by an individual firm is then affected by the switching activity. Second, high energy costs may hinder the profitability of local firms, resulting in a low GDP growth and tax contribution. Local authorities then have a motive to lower the real electricity price through ways such as short-term preferential prices, subsidies and tax refunds. As a result, if the observable electricity prices are higher than the real electricity prices, then we may underestimate the price effect of electricity on switching behaviour.

The potential for electricity prices to be affected by firm behaviour presents a challenge in analyzing the causality between electricity costs and switching behaviour. As a result, the endogeneity caused by both sources may induce a downward bias and underestimation of the price effect. The endogeneity of the energy price is also mentioned by Abeberese (2012), Ganapati et al. (2016) and Allcott et al. (2016). Abeberese (2012) interacts the coal price and the thermal power generation capacity to create an instrument for India electricity prices. Similarly, Ganapati et al. (2016) interact three types of fuel prices (coal, natural gas and petroleum) and the shares of fuel used to generate electricity respectively as instruments for U.S. state-level electricity prices. In their study of the impact of electricity shortages on India manufacturing firms, Allcott et al. (2016) use the average state level shortage of

[6] Strictly speaking, the subscripts for $Productivity^N_{st}$, $KL\ ratio^N_{st}$, $Size^N_{st}$, SOE^N_{st}, FIE^N_{st},EXP^N_{st} and $R\&D^N_{st}$ are $ispt$ since the algorithm varies for each individual firm. For the consistency of expression, we use the subscript st for all industrial characteristics.

hydroelectric power availability as an instrument. For China, a significant proportion of the electricity generated comes from thermal power plants which use coal as the main source of fuel. During our period, electricity generation from coal accounted for around 80% of total electricity generation (World Bank, 2014). Although the coal price affects generation costs to a large extent, the electricity sales price does not capture the frequent fluctuations in coal prices because coal prices are market driven while electricity prices are highly regulated. As a result, we use the interaction between coal production and thermal power generation capacity as an instrument for provincial industrial electricity prices.

$$IV_{pt} = Coal\ production_{pt} \times Thermal\ power\ generation\ capacity_{pt} \tag{3.8}$$

$$Capacity_{pt} = \frac{Electricity\ generation\ from\ coal_{pt}}{Electricity\ generation\ from\ all\ types\ of\ fuel_{pt}} \tag{3.9}$$

As before subscripts p, t signify that variables at the provincial level in year t. The instrument is expected to have a negative impact on energy prices. Definitions of our variables can be found in Table B.1 in the appendix.

3.4 Data

In this section we provide a brief introduction to the two main dataset that we use in the paper. The first is the Chinese Industrial Enterprises Dataset classified by the Chinese Industrial Classification (CIC) system. Complied and issued by NBSC, national economic activities are broken down by industry. At the 2-digit level the manufacturing sector is coded from 13 to 43. The annual survey provides detailed performance variables such as industrial output, export value, fixed assets and investments for all "above scale" industrial firms in China.[7]

[7]The scale defined for Chinese Industrial Enterprise Dataset indicates firms with annual sales no less than 5 million RMB until 2011 when the standard was raised to 20 million RMB.

To clean the data we follow Brandt et al. (2012). First we link firms from annual surveys with IDs and then match firms that might have changed their IDs as a result of restructuring, merger or acquisition using other information such as firms' name, legal person name, post code, phone number etc. Then we drop observations where key variables are negative and firm survival is less than two years between 2005 and 2007.[8] Table 3.2 compares the output aggregates at the 2-digit level between the enterprises dataset and the NBSC website. Manufacture of tobacco (16) and Recycling and disposal of waste (43) are dropped because of insufficient coverage and a relatively small total industrial output. After dropping outliers following similar methods in Brandt et al. (2012) the result is a dataset with 261,786 firms covering 28 2-digit manufacturing sectors. The energy intensity information at the 2-digit level can be found in Table B.2 in the appendix.

[Table 3.2 about here]

Table 3.3 presents an overview of switching behaviour. On average approximately 2.7% of firms change their main product per year.[9] More switching happens from high EI industries to low EI industries and the EI gap tends to be larger when the switching is from a high EI industry to a low EI industry. Table 3.4 presents the results from a significant test that shows that the mean of the EI gap of group "Switching to a low EI industry" is significantly different to the mean for the group "Switching to a high EI industry".

[Table 3.3 about here]

[Table 3.4 about here]

[8]Key variables include industrial output, sales, value added, intermediate, employment,fixed capital, depreciation, the share that is state-owned, Foreign or from Hong Kong, Macao and Taiwan, export and R&D expenditure.

[9]Newman et al. (2013) finds a 6 to 35 percentage of switching for Vietnamese manufacturing firms between 2001 and 2008.

The second dataset we use is the industrial electricity price dataset, released by the China Price Information Center (CPIC) under NDRC. It provides the retail price for industrial electricity of 35kV and above for 36 large and medium sized cities or province-equivalent municipal cities.[10] We use the average province price aggregated across the cities in that province to represent the industrial electricity price level of that province. This allows us to consider the role of the provincial government in energy pricing.[11]

Table B.3 in the appendix provides a brief description of province electricity prices and the relationship between the industrial electricity price, thermal power generation capacity and coal production for individual provinces. The average industrial electricity price is 627 yuan/MWH in 2005 prices. For our thermal power generation variable, we observe that Shanghai, Tianjin and Shandong have the electricity fully powered by coal. Shanxi produces on average 588 billion tons of coal and is the top producer in China. In Figure 3.1 we plot the industrial electricity price which we represent geographically in Figure 3.2. Figure 3.1 shows that the average electricity price rose smoothly relatively between 2005 and 2012 including during our period 2005 to 2007. After 2009 there is evidence of greater price dispersion across provinces. Figure 3.2 shows that the east and the southern areas of China have generally higher electricity costs than the north and the west area. Figure 3.3 provides an overview of the inverse relationship between IEP and our instrument. The validity of instrument is checked later using post-regression tests. Finally, Table 3.5 provides summary statistics for our control variables. A correlation matrix can be found in Table B.4 of the appendix.

[Figure 3.1 about here]

[10] The 36 large and medium size cities comprise 31 province-equivalent municipalities or provincial capitals, and 5 large non-capital cities including Qingdao (Shandong province), Ningbo (Zhejiang province), Dalian (Liaoning province), Shenzhen (Guangdong province) and Xiamen (Fujian province).

[11] Electricity pricing in China is mainly controlled by NDRC and provincial governments. Province-level officials set electricity prices taking account inflation, industrial support and social stability under the instruction of NDRC. For more information about energy pricing in China, see Fredrich Kahrl (2011); US ITC (2007); IEA and OECD (2006).

[Figure 3.2 about here]

[Figure 3.3 about here]

[Table 3.5 about here]

3.5 Empirical Results

3.5.1 Preliminary investigation

If firms expect continuously rising energy prices they have an incentive to adjust production to produce goods in industries that are less energy intensive. Our investigation of the impact of electricity prices on switching using traditional estimation methods is presented in Table 3.6. The dependent variable is switching dummy that is of 1 if a firm switched to a different main product at the 4-digit level. We include 4-digit industry fixed effects, province fixed effects and year fixed effects. Standard errors are clustered at the firm level.

Column (1) in Table 3.6 presents the results including only IEP and fixed effects at different levels on the right hand side.[12] Firm-level characteristics and industry-level characteristics are added in column (2) - (5). For robustness we employ two measures of productivity (TFP and labour productivity) and two series of measurements for the ownership, exports and R&D expenditure (share variables and dummies). The pooled OLS results show a statistically significant and positive impact of IEP on firms' switching probability. A 10% increase

[12] With the binary dependent variable, linear probability model (LPM) is not bounded with the unit interval and it does not estimate the structural parameters of non-linear models. While since our interest lies on the marginal effects rather than structural parameters and LPM often does a good job on marginal effect estimation (Wooldridge, 2010, pp 563), we use LPM in the present study. Using a trimmed sample with log transformation and cluster-robust standard errors we hope to ease the possible bias due to heteroscedasticity induced by LPM to some extent(Horrace and Oaxaca, 2006). We replicate Table 3.6 using Probit method and the results are presented in Table B.5. The parameters of variables of interest are highly significant and consistent across different specifications.

in electricity prices increases the probability of a firm switching by approximately 0.54%. Results are highly consistent and statistically significant across different specifications. As shown in Table B.3, the province with the highest annual industrial electricity price in our sample is Guangdong (772.9 Yuan/MWh) and Inner Mongolia has the lowest price level (444.4 Yuan/MWh). As a result, everything else equal, the switching probability of firms located in Guangdong is approximately 9.4 percentage points higher than firms from Inner Mongolia due to electricity cost differences.

Our results also show that the overall impact also depends on the current EI level of an industry. The positive coefficient of the interaction term between IEP and EI shows that firms from energy intensive industries are more likely to be affected by high energy costs and hence are more likely to adjust their main product. For example, from Table B.2 we know that Sector 33-Smelting and processing of non-ferrous metals has an EI that is around ten times higher than Sector 40 which has the lowest EI. It implies that for two firms sharing similar characteristics, located in the same province but operating in these two sectors respectively, the probabilities of switching industries of these two firms differ by roughly 13%. It is intuitive that in industries where energy costs are a large proportion of total costs, firms are more sensitive to electricity price changes.

Turning to the other right hand side variables, the coefficients and significance levels are relatively stable across different specifications. We consider further the firm-level characteristics. Both of our productivity measures, total factor productivity and value added per worker, significantly increase the probability of the switching. A 10% increase in productivity increases the probability of switching by 0.024%. Our results are in line with Newman et al. (2013) who argue that productivity is a critical factor for firms to consider staying with the same product or switching, or even to exit the market, and show for Vietnam that firms with 1% higher TFP tend to increase the switching probability by 0.021 percentage points during the eight years from 2001 to 2008. The capital labour ratio is found to have a negative impact on switching and firm size shows a positive influence on the switching decision. One implication is that switchers tend to be the large labour intensive firms in our sample which is partly in line with Newman et al. (2013) who find that switchers tend to be small labour intensive firms. Turing to the multi-product firms that account for nearly 30 percent of firms in our sample, we find as expected that firms operating with multiple products are more likely to switch their main production when facing the electricity price changes.[13]

Considering ownership we find that firms with a large share of state ownership are less likely to switch products compared with mainly domestic firms. The probability of switching falls by roughly 0.10 percentage points if there is a 10% increase in the share of state ownership. A similar result has been found when we include a SOE dummy which is assigned as unit value when state owned investment share is greater than 51%. On average a state owned firm is less likely to switch their main product by approximately 0.88 to 0.89 percentage points. For foreign ownership, Column (2) and column (3) show that on average a 10% increase in foreign investment share and a 10% increase in exports as a share of total output leads to an approximately 0.025 and 0.027 percentage point increase in the switching probability, respectively. However, the FIE and export dummy variables are insignificant.[14] Finally, although R&D expenditure is considered to be an important factor that affects firm performance such as the entry and exit decisions (Klepper, 1996; Agarwal and Audretsch, 2001), we find no significant impact of R&D expenditure (share and dummy variables) on the switching decision at individual firm level.

[13]In Chinese industrial firm dataset the 4-digit sector code is assigned based on the product which accounts for the highest share of total revenue while no quantity or value information is provided for products other than the main product. There are variables recording firm's main product 1, main product 2 and main product 3. However, the records are imported in Chinese without a uniform codebook (roughly at the 2 to 3 digit level). The dummy variable MULTI is simply defined as dummy with unit value if the firm has multiple records in product types.

[14]The inconsistency may be due to the less variation in our sample when both of the dependent and independent variables are measured by dummy variables.

We now turn to our industry controls. We find a negative coefficients on average industry firm size shows that firms tend to stay in industries where the average firm size is large. A possible explanation might be the high sunk costs of establishing market positions in these industries. High sunk costs act as a barrier to exit as well as to entry, because these costs can not be recovered if a firm decides to leave an industry (Eaton and Lipsey, 1980). It commits the entrant to stay in the market and gradually invest more to experience higher expected growth rates (Cabral, 1995; Cabral and Ross, 2008). For our ownership variables, we find strong evidence that firms tend to switch out from industries with a high foreign presence. Given the fact that at the individual level SOEs are less likely to switch, we conclude that it is mainly private firms that are crowed out from industries with large share of foreign ownerships.[15] For exports, we observe that firms are less likely to switch out from strongly export-oriented industries. Some evidence shows that firms have a higher tendency to switch if they have a higher share of R&D expenditure over total output.[17] Concentration ratio and industrial EI levels have no effect.

[Table 3.6 about here]

3.5.2 Switching directions

In the previous section we find that the electricity price plays an significant role in affecting firm's switching decision. However, we have not considered the direction of the impact although we assume that higher electricity prices promote firms to switch from producing

[15]Existing foreign presence can also prevents new foreign entrants (Mitchell et al., 1994; Shaver et al., 1997; Mata and Portugal, 2002; Chang and Xu, 2008). For example, Mitchell et al. (1994) argues that both a low and a high foreign market share are not suitable for new foreign entrants due to the lack of market information and the increasing congestion effects.[16] The phenomenon of crowding-out foreign investments has also been found among Chinese manufacturing firms (Chang and Xu, 2008).

[17]The inconsistency of the significance on R&D share and dummy variables may be due to the large amount of zero values of R&D expenditure in out dataset. We generally consider R&D expenditure has insignificant effect on firms' switching behaviour.

high EI goods to low EI goods. Table 3.7 and 3.8 presents the results on switching directions using the traditional method. The dependent variable *Switch_HL* in Table 3.7 is a dummy that equals to one when a firm switches into a less energy intensive industry, and zero for non-switchers. Correspondingly, the dependent variable *Switch_LH* in Table 3.8 captures the switching behaviour from a less energy intensive industry to a more energy intensive industry.

The positive and significant coefficients of IEP in Table 3.7 confirm our prediction that higher electricity costs drive firms away from producing energy intensive goods. Firms located in provinces with high IEP are more likely to switch to a less energy intensive industry everything else equal. The coefficient on IEP ranges from 0.074 to 0.075, which suggests that with a 10% electricity price increase the probability of firm switching their main product into a less energy intensive industry rises by approximately 0.74%. The insignificant interaction term between IEP and EI shows that there is no additional incentive for firms in energy intensive industries to switch out merely because of high electricity costs.

Table 3.8 presents the results for switching to a more energy intensive industry. The results show that firms are more likely to switch to a high EI industry if they experience a high electricity price. The positive and significant coefficients on IEP suggest that with a 10% increase in IEP the probability that a firm switches to a more energy intensive industry rises by about 0.85% to 0.92%. This is against our priors that firms located in provinces with costly electricity should be less likely to drop their current main products and switch into productions that rely heavily on electricity instead. The abnormal coefficients on IEP in Table 3.8 suggest that there might be a severe misspecification. We consider the observable IEP is inappropriate for the evaluation of price effects. The misspecification bias occurs due to the ignorance of unobservable government impacts using the traditional estimation method. The investigation in the next section shows that the intervention from local authorities distorts the price impact by hindering firms' incentive to switch to a low EI industry and encouraging firms to stay in a high EI industry.

In terms of other controls, we generally find consistent results comparing to those in Table 3.6 in the previous section. Our results show that large multi-product firms with high productivity are more likely to switch to both a more and less energy intensive industries. SOEs are generally less likely to switch their main products in both cases. However, we do find some differences in the determinants of switching behaviour. For example, firms that switch to a low EI industry tend to be more productive than the average. Negative coefficients on KL ratio in Table 3.7 suggest that labour intensive firms are more likely to switch to a low EI industry. In other words, capital intensive firms are more likely to stay within producing energy intensive goods. A possible explanation could be the corresponding competitive advantage of capital intensive firms in energy intensive industries (Cole and Elliott, 2003; Cole et al., 2005). On the contrary, exporters are more likely to switch to low EI industry everything else equal. These features do not stand up for switching behaviour to a more energy intensive industry in Table 3.8.[18] As for the industry-level characteristics, some evidence suggests that firms operating in a industry with large foreign ownership share are more likely to switch to an energy intensive industry which corresponds to our previous findings in Table 3.6.

[Table 3.7 about here]

[Table 3.8 about here]

[18]The share of R&D expenditure over total output shows a negative and significant impact on switching to a less energy intensive industry. However, R&D dummy indicates a insignificant effect. As we mentioned this may be due to a large amount of zero value of R&D expenditure in our sample and we consider R&D expenditure has insignificant effect in general.

3.5.3 The endogenous electricity price in China

As we have discussed previously, provincial energy prices may be endogenous due to the policy-oriented pricing scheme in China. Hence, an instrument is employed to address the potential endogeneity issue, namely the interaction term of provincial coal production and thermal power generation capacity. Thermal power generation capacity is not expected to have a direct impact on the decision of local firms other than the link to electricity; the amount of coal production is determined by geographical factors and as a consequence, no immediate influence on firms production is expected.

We use the under-identification test (Kleibergen-Paap rk LM statistic) and the weak-identification test (Kleibergen-Paap Wald rk F statistic) to test for the validity of our instrument. With null hypothesis that the matrix is not full column rank, a rejection of the null indicates that the model is identified. The null hypothesis for weak-identification test is that the instrument is only weakly correlated with the endogenous variable and a large F statistic that exceeds the Stock-Yogo critical values eliminates the weak identification concern.[19] The rejection of the under-identification test and weak-identification test suggest that our instrument is valid. Coal production and thermal power generation capacity jointly play a significant role in determining regional electricity prices. In the meanwhile they are exogenous from regional firms' decision about switching.

Table 3.9 and Table 3.10 present the 2 stage least square (2SLS) results for switching to a less and a more energy intensive industry respectively. The coefficients on IEP remains highly significant at the 1% level for both switching directions. However, comparing with the OLS results, the 2SLS coefficients on IEP rises substantially for switching to a less energy intensive industry, and show an opposite impact on switching to a more energy intensive

[19]The Stock-Yogo critical values for F statistics calculated after each 2SLS regression are available upon request. The F statistic in all specifications in our study pass the weak-identification test.

industry. The instrumented coefficients suggest that a 10% increase in IEP leads to a 2.34% to 2.42% increase in the probability of switching to a less energy intensive industry, and a 2.12% to 2.24% fall of the probability of switching to a more energy intensive industry everything else equal. Furthermore, the negative and significant coefficients on the interaction term in Table 3.10 suggest that the dampening effect of IEP rises as the firm's initial EI level increases.

The comparison between results under OLS estimation and IV estimation shows that the endogeneity on electricity prices has not only lowered the incentive of firms to switch to less energy intensive industries, but also distorted the restrictive effect of IEP on stopping firms from switching to more energy intensive industries. The reversed sign of coefficients of the electricity price indicates the severe misspecification of OLS estimation and emphasizes the unobservable government impacts on regional electricity prices. Our finding together with previous literature shows that it turns out the local energy intensive industries are protected by governments' preferential energy prices and other supportive policies such as subsidies. IEP has become a political tool for local authorities to promote the development of energy intensive industries. The preferential electricity price and negotiated price were prevalent across provinces during the period of our study. Although NDRC instituted policies to increase electricity prices charged for energy intensive industries in 2004, significant resistance by local authorities to implementing these surcharges has implied a general failure of these initial attempts. Provincial and local officials maintained a strong incentive in providing reduced utility fees to heavy industries operating within their localities because of the jobs, tax revenues and personal payoffs provided by these firms (US ITC, 2007; IEA and OECD, 2006; Zhang, 2011).

As for the firm-level characteristics in Table 3.9 and 3.10, the parameters are highly consistent with the OLS estimation in Table 3.7 and 3.8 in terms of both statistical significance and magnitude. Switchers tend to be large, productive firms with a low capital-labour ratio (for firms switching to a less energy intensive industry) other conditions equal. SOE firms are also found to be less likely to switch their main product. Some evidence shows that firms with a high share of exports over total output are more flexible and tend to switch to a less energy intensive industry. R&D expenditure shows insignificant effect in general.

Comparing industrial characteristics, coefficients that are significant in Table 3.7 and 3.8 remains statistically significant with our IV estimations. Firms operating in energy intensive industries with large competitors are less likely to switch out generally to both directions. In terms of ownership structure, industries with a large share of state-owned ownership are less likely to have firms switching to a low EI industry but more likely to have firms switching to a high EI industry. This may be due to the fact that most of the key energy-related heavy industries are state-owned. Firms that compete in industries with large share of foreign ownerships are also more likely to switch to a energy intensive industry. R&D expenditure is generally insignificant and the concentration ratio measured by the top 5% firms' output over total industrial output is insignificant in any specification.

[Table 3.9 about here]

[Table 3.10 about here]

3.5.4 Robustness checks

To provide reliable evidence of the price effect, we conduct two series of estimations for robustness check. First, we examine the relationship between IEP and the extent of the change in EI that firms switch across. The dependent variable is the EI gap defined in Section 3.3.1 – the absolute electricity intensity difference between the present industry and the aimed industry for switchers, and zero for non-switchers. This can be considered as a measure of the difficulty a firm faces when switching its main product. Table 3.11 and 3.12 presents the results on EI gap using OLS and 2SLS methods respectively. For simplicity's sake, we keep the results using ownership dummies in this section. For simplicity's sake, we use dummy variables only instead of both share and dummies to represent the ownership structure. The first three regressions in Column (1) to (3) include switchers to low EI industries and and non-switchers; the remaining three columns cover switchers to high EI industries and non-switchers.

The results are highly consistent with those using $Switch\_HL$ and $Switch\_LH$ as dependent variables under OLS and 2SLS estimations respectively. The price effects are positive and significant for promoting switching to a low EI industries. The coefficients on IEP with our 2SLS estimation in column (2) and (3) of Table 3.12 are nearly three times higher than those under OLS estimation. In our preferred method (Column (2) and (3) of Table 3.12), a 10% IEP increase leads to a 11.03% to 11.05% increase in the EI gap that a firm switches across to a low EI industry. As for switching to a more energy intensive industry, as indicted previously, OLS estimation and IV estimation reveal contrasting price impacts. With our 2SLS estimation in Columns (5) and (6) of Table 3.12, a 10% increase in IEP means that the EI gap to a high EI industry pulls by approximately 17.77%. The results of other controls also match those observed in earlier estimations.

[Table 3.11 about here]

[Table 3.12 about here]

The second series of robustness checks is based on a smaller sample that excludes all SOEs and the top 10% largest firms. Table 3.13 and 3.14 present the results on switching directions with the subsample using OLS and 2SLS methods respectively. These results again are highly consistent with previous findings. Overall, our confirm the association between IEP and firms' switching behaviour, and further support our idea of endogenous electricity prices.

[Table 3.13 about here]

[Table 3.14 about here]

3.6 Conclusions

In this paper we investigate how energy prices affect manufacturing firms' behavior in Chinese provinces between 2005 and 2007. Specifically, we test the impact of industrial electricity price on firms' production choice under exogenous energy prices variability. By considering the potential endogeneity arising from the policy-oriented pricing regime in China, our results suggest that industrial electricity prices act as an effective intervention that could be used to promote the shifting of the industrial structure towards a energy efficient structure.

Evidence shows that the more expensive energy not only provides a strong incentive for firms to switch into less energy intensive industries, but also prevents firms from switching into more energy intensive industries. A 10% electricity price increase is found to increase the probability of switching to a less energy intensive industry by approximately 2.34% to 2.42%, and reduce the probability of switching to a more energy intensive industry by 2.12% to 2.24%. The prevention effect also strongly depends on a firm's current energy intensity level. The higher the current energy intensity is, the less likely that a firm in a province with costly electricity will switch to a even more energy intensive industry. The price effect is statistically significant and robust under different specifications

A number of firm characteristics and industrial characteristics are also shown to have significant impacts on firms' switching decision. Our results suggest that switchers tend to be large and more productive firms. SOE firms are generally less likely to switch their main product. Labour intensive firms and exporters tend to switch out to seek opportunities in less energy intensive industries. At the industry level, firms operating in industries with large competitors are less likely to switch generally, while firms in industries with large shares of state-owned and foreign ownerships are more likely to switch into high EI industries.

An important finding is the evidence of the preferential electricity price used by provincial and local authorities to support their jurisdictional energy intensive industries. By comparing results from OLS estimation with 2SLS estimation, the prevention effect of costly energy has been reversed as a result of endogenous linkage between firm performance and energy prices. This finding suggests that an ignorance of the local protectionism and the conflict of interest between the central and local authorities in China could lead to a biased evaluation of national-wide policies.

Furthermore, in the period of our study most of our provinces experienced a steady price increase. Over time the IEP of the majority of provinces continues an upward trend and the price difference between them has become smaller. Nevertheless, the price difference between province at the bottom and the majority has actually become larger as shown in Figure 3.1, especially in the recent years. As a result, there is a larger price variation across Chinese provinces. North and west provinces such as Inner Mongolia and Shanxi actually experienced price falls comparing to the south and eastern regions. Given the price impact on the industrial structure, it may cause energy intensive industries to shift from the south-east to the north-west. In fact, the westward movement of energy intensive firms in China has been found in the work of Wu et al. (2017).

Finally, the ongoing energy market reform aims at fostering competition in energy sectors and a decreasing of energy prices is expected throughout the country. Take the recent electricity transmission and distribution pricing reform as an example. The reform, first rolled out in Shenzhen in 2014, aimed at taking the monopoly power from grid companies and allowing room for the market to decide prices on both generation and consumption sides. Lower electricity prices may lead to an increasing of energy consumption which offsets the efficiency improvement and make it more challenging of improving energy efficiency. Along with energy pricing reforms, supplementary policies on promoting energy diversification and investment in energy-saving technology shall be further strengthened. Due to the high generation costs the market share of renewable energy is limited. Once the negative externality of fossil energy is internalized properly, unconventional energy is expected to play a more important role in China's energy market. Accelerating the replacement of laggard production equipment and encouraging innovation is another important way to bolster energy efficiency and control environmental pollution. Rebalancing the economy towards a less energy-hungry growth mode are effective means to curb pollution and to control carbon emissions that cause global warming.

Figures and tables

Fig. 3.1 Industrial electricity price trend in China (2005-2012)

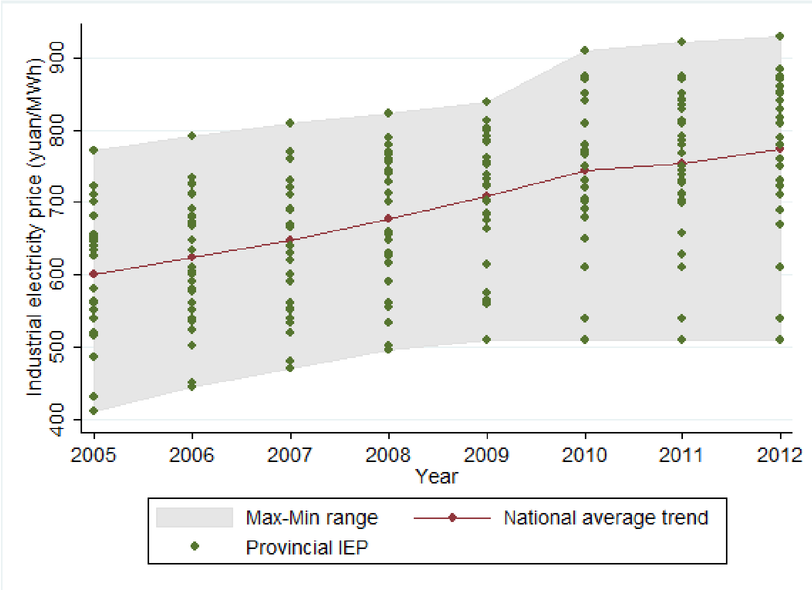

Fig. 3.2 Annual average electricity price in China (2005-2007)

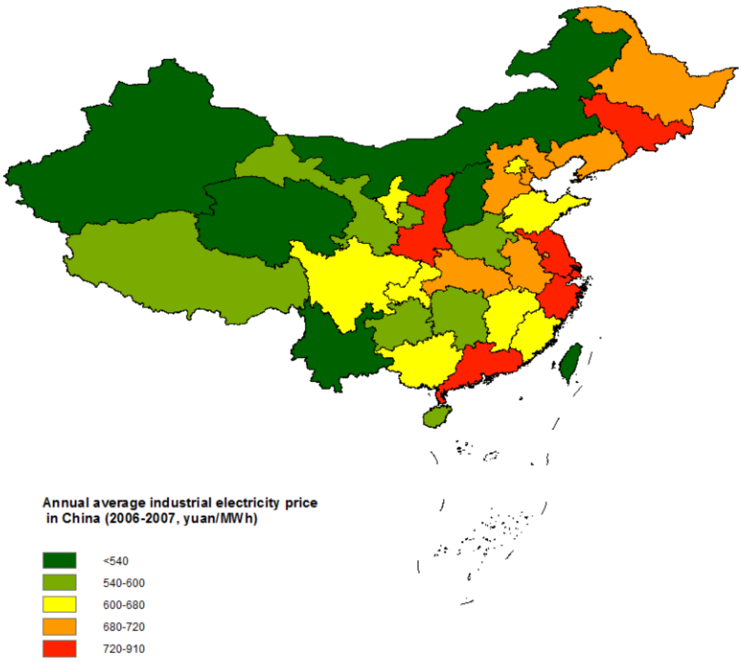

Fig. 3.3 Industrial electricity price and the instrument (2005-2007)

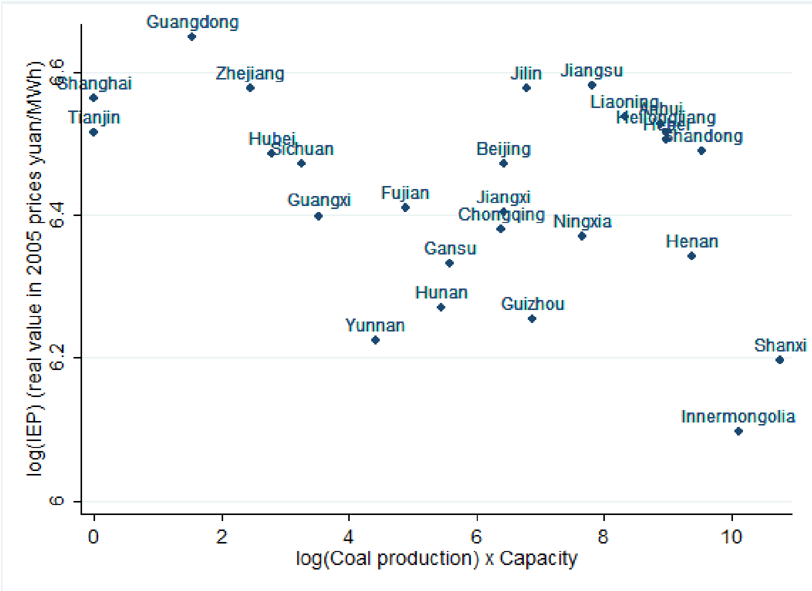

Table 3.1 Definition of switching behaviour

Year 2005	Year 2006	Year 2007
Edible vegetable oil processing (CIC 1311) *Switch = 0*	Edible vegetable oil processing (CIC 1311) *Switch = 1*	Non-edible vegetable oil processing (CIC 1312) *Switch* = .
Edible vegetable oil processing (CIC 1311) *Switch = 1*	Non-edible vegetable oil processing (CIC 1312) *Switch* = .	Non-edible vegetable oil processing (CIC 1312) *Switch* = .
Edible vegetable oil processing (CIC 1311) *Switch = 0*	Edible vegetable oil processing (CIC 1311) *Switch = 0*	Edible vegetable oil processing (CIC 1311) *Switch = 0*

Table 3.2 Sectoral output comparison from different data sources

CIC2	Sector output from NBSC	Aggregated output from firm level	Percentage	CIC2	Sector output from NBSC	Aggregated output from firm level	Percentage
13	13695	12538	91.55	28	3312	3173	95.83
14	4855	4512	92.94	29	2797	2659	95.07
15	4024	3786	94.09	30	6523	6047	92.7
16	3277	2497	76.19	31	12159	11198	92.1
17	15573	14692	94.34	32	26859	25338	94.34
18	6245	5846	93.61	33	12969	11738	90.51
19	4255	4016	94.38	34	8844	8207	92.79
20	2592	2347	90.52	35	14254	13466	94.47
21	1912	1760	92.06	36	8210	7613	92.72
22	5174	4851	93.76	37	21082	19761	93.73
23	1756	1643	93.57	39	18695	17628	94.29
24	1780	1689	94.9	40	33099	31547	95.31
25	15000	9732	64.88	41	3543	3392	95.76
26	21202	19395	91.47	42	2652	2454	92.53
27	5210	4953	95.05	43	464.6	412.6	88.8

[a] 2005-2007 annual average. 16-Manufacture of tobacco and 43-Recycling and disposal of waste are dropped because of insufficient coverage and relatively small total industrial output.

Table 3.3 Summary of switching behaviour (2005-2007)

	2005	2006	Total
Number of firms	258,260	240,757	261,786
Switchers	6,775	6,648	13,175
Percentage of all firms (%)	2.62	2.76	5.03
	Numbers of firms	Mean of EI gap	
Switching to a low EI industry	6,870	409	
Switching to a high EI industry	6,305	293	

Note: EI gap unit Kwh/10000 yuan.

Table 3.4 Linear restriction test of equal EI gap

EI gap	Coef.	Std. Err.	t	$p > \|t\|$	[95% Conf. Interval]	
Switching to a low EI industry	0.041	0.001	75.311	0	0.04	0.042
Switching to a high EI industry	0.029	0.001	46.808	0	0.028	0.031

$$H_0 : \beta_1 - \beta_2 = 0$$
$$F(1, 11889) = 198.72$$
$$Prob > F = 0.0000$$

Table 3.5 Summary statistics (2005-2007)

Variable	Obs	Mean	Std.Dev.	Min	Max
IEP	457,022	680.12	68.53	431.67	790.56
Coal production	457,022	5,018.65	7,601.51	0.00	58,141.91
Capacity	457,022	0.84	0.17	0.36	1.00
TFP	457,022	6.54	1.00	2.00	11.53
Labour productivity	457,022	99.46	122.60	4.63	1,031.82
KL ratio	457,022	78.68	108.56	0.70	1,002.06
Size	457,022	16,797.92	61,382.54	8.00	3,125,911.00
SOE share	457,022	0.03	0.16	0.00	1.00
FIE share	457,022	0.17	0.35	0.00	1.00
EXP share	457,022	0.18	0.35	0.00	1.00
R&D share	457,022	0.01	0.05	0.00	0.77
SOE dummy	457,022	0.03	0.17	0.00	1.00
FIE dummy	457,022	0.16	0.37	0.00	1.00
EXP dummy	457,022	0.30	0.46	0.00	1.00
R&D dummy	457,022	0.30	0.46	0.00	1.00
CR	457,022	0.38	0.07	0.09	0.94
EI	457,022	0.06	0.05	0.00	0.46

Table 3.6 Effect of industrial electricity price on switching (Pooled OLS)

VARIABLES	(1) Switch	(2) Switch	(3) Switch	(4) Switch	(5) Switch
Log(IEP)	0.0640***	0.0529***	0.0530***	0.0544***	0.0544***
	(0.0117)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
Log(IEP) × EI		0.1300**	0.1304**	0.1266**	0.1270**
		(0.0571)	(0.0571)	(0.0571)	(0.0571)
Firm-level controls					
TFP		0.0024***		0.0024***	
		(0.0004)		(0.0004)	
Log(Labour productivity)			0.0023***		0.0023***
			(0.0004)		(0.0004)
Log(KL ratio)		-0.0009	-0.0028***	-0.0011**	-0.0030***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
Log(Size)		0.0020***	0.0035***	0.0022***	0.0037***
		(0.0005)	(0.0004)	(0.0005)	(0.0004)
Multi		0.0068***	0.0068***	0.0068***	0.0068***
		(0.0009)	(0.0009)	(0.0009)	(0.0009)
SOE share		-0.0097***	-0.0098***		
		(0.0021)	(0.0021)		
FIE share		0.0025**	0.0025**		
		(0.0012)	(0.0012)		
EXP share		0.0027**	0.0027**		
		(0.0012)	(0.0012)		
R&D share		-0.0052	-0.0053		
		(0.0064)	(0.0064)		
SOE dummy				-0.0088***	-0.0089***
				(0.0020)	(0.0020)
FIE dummy				0.0008	0.0008
				(0.0011)	(0.0011)
EXP dummy				0.0005	0.0005
				(0.0009)	(0.0009)
R&D dummy				0.0000	0.0000
				(0.0008)	(0.0008)
Industry-level controls					
TFP^N		0.0132		0.0116	
		(0.0094)		(0.0094)	
Log(Labour productivity)^N			0.0129		0.0122
			(0.0097)		(0.0097)
Log(KL ratio)^N		0.0254	0.0149	0.0153	0.0058
		(0.0140)	(0.0142)	(0.0143)	(0.0145)
Log(Size)^N		-0.0644***	-0.0557***	-0.0568***	-0.0489***
		(0.0125)	(0.0127)	(0.0126)	(0.0128)
SOE share^N		-0.0925	-0.0944		
		(0.0625)	(0.0624)		
FIE share^N		0.1728***	0.1727***		
		(0.0448)	(0.0448)		
EXP share^N		-0.1178***	-0.1186***		
		(0.0302)	(0.0302)		
R&D share^N		0.5592***	0.5527***		
		(0.1622)	(0.1618)		
SOE dummy^N				-0.0561	-0.0580
				(0.0579)	(0.0578)
FIE dummy^N				0.1638***	0.1635***
				(0.0394)	(0.0394)
EXP dummy^N				-0.0962***	-0.0967***
				(0.0235)	(0.0234)
R&D dummy^N				-0.0048	-0.0046
				(0.0202)	(0.0202)
CR		-0.0177	-0.0179	-0.0190	-0.0192
		(0.0148)	(0.0148)	(0.0148)	(0.0147)
EI		-0.6341	-0.6373	-0.6083	-0.6104
		(0.3667)	(0.3669)	(0.3664)	(0.3666)
Constant	-0.4067***	-0.0305	-0.0327	-0.0369	-0.0431
	(0.0756)	(0.1166)	(0.1194)	(0.1169)	(0.1196)
Observations	457,022	451,198	451,198	451,198	451,198
Adjusted R-squared	0.0291	0.0308	0.0307	0.0307	0.0307
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
No. of clusters	256,053	255,832	255,832	255,832	255,832

Note: Standard errors clustered at firm level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications.

Table 3.7 Effect of industrial electricity price on switching to a less energy intensive industry (Pooled OLS)

VARIABLES	(1) Switch_HL	(2) Switch_HL	(3) Switch_HL	(4) Switch_HL	(5) Switch_HL
Log(IEP)	0.0737***	0.0746***	0.0745***	0.0740***	0.0739***
	(0.0170)	(0.0171)	(0.0171)	(0.0172)	(0.0172)
Log(IEP) $\times$ EI		0.0049	0.0051	0.0038	0.0041
		(0.0546)	(0.0546)	(0.0544)	(0.0544)
Firm-level controls					
TFP		0.0005**		0.0005**	
		(0.0002)		(0.0002)	
Log(Labour productivity)			0.0004		0.0004
			(0.0002)		(0.0002)
Log(KL ratio)		-0.0012***	-0.0016***	-0.0013***	-0.0016***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Log(Size)		0.0011***	0.0014***	0.0010***	0.0014***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Multi		0.0031***	0.0031***	0.0030***	0.0030***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
SOE share		-0.0029**	-0.0029**		
		(0.0012)	(0.0012)		
FIE share		0.0005	0.0005		
		(0.0007)	(0.0007)		
EXP share		0.0023***	0.0023***		
		(0.0007)	(0.0007)		
R&D share		-0.0092***	-0.0093***		
		(0.0032)	(0.0032)		
SOE dummy				-0.0028**	-0.0029**
				(0.0012)	(0.0012)
FIE dummy				-0.0001	-0.0001
				(0.0006)	(0.0006)
EXP dummy				0.0013**	0.0013**
				(0.0006)	(0.0006)
R&D dummy				0.0001	0.0001
				(0.0005)	(0.0005)
Industry-level controls					
TFP^N		-0.0022		-0.0038	
		(0.0121)		(0.0119)	
Log(Labour productivity)^N			-0.0022		-0.0032
			(0.0124)		(0.0123)
Log(KL ratio)^N		0.0079	0.0097	0.0012	0.0040
		(0.0173)	(0.0174)	(0.0182)	(0.0180)
Log(Size)^N		-0.0272	-0.0286	-0.0209	-0.0232
		(0.0141)	(0.0151)	(0.0147)	(0.0153)
SOE share^N		-0.1289	-0.1286		
		(0.0766)	(0.0765)		
FIE share^N		-0.0540	-0.0540		
		(0.0459)	(0.0459)		
EXP share^N		-0.0158	-0.0157		
		(0.0328)	(0.0327)		
R&D share^N		0.3531**	0.3538**		
		(0.1665)	(0.1656)		
SOE dummy^N				-0.1003	-0.0998
				(0.0711)	(0.0710)
FIE dummy^N				-0.0307	-0.0307
				(0.0401)	(0.0401)
EXP dummy^N				-0.0321	-0.0321
				(0.0277)	(0.0277)
R&D dummy^N				-0.0150	-0.0150
				(0.0222)	(0.0222)
CR		0.0018	0.0018	0.0019	0.0020
		(0.0165)	(0.0165)	(0.0167)	(0.0167)
EI		0.0321	0.0322	0.0340	0.0347
		(0.0653)	(0.0653)	(0.0646)	(0.0645)
Constant	0.0299***	0.2318**	0.2326**	0.2246**	0.2231**
	(0.0083)	(0.1065)	(0.1121)	(0.1051)	(0.1106)
Observations	457,022	451,198	451,198	451,198	451,198
Adjusted R-squared	0.0158	0.0167	0.0167	0.0166	0.0166
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
No. of clusters	9,325	9,249	9,249	9,249	9,249

Note: Standard errors clustered at province-industry level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications.

Table 3.8 Effect of industrial electricity price on switching to a more energy intensive industry (Pooled OLS)

VARIABLES	(1) Switch_LH	(2) Switch_LH	(3) Switch_LH	(4) Switch_LH	(5) Switch_LH
Log(IEP)	0.0917***	0.0854***	0.0854***	0.0867***	0.0867***
	(0.0183)	(0.0193)	(0.0193)	(0.0193)	(0.0193)
Log(IEP) × EI		0.0850***	0.0851***	0.0861***	0.0862***
		(0.0317)	(0.0317)	(0.0316)	(0.0316)
		Firm-level controls			
TFP		0.0004		0.0005	
		(0.0002)		(0.0002)	
Log(Labour productivity)			0.0004		0.0004
			(0.0002)		(0.0002)
Log(KL ratio)		0.0004	0.0001	0.0003	-0.0000
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(Size)		0.0008***	0.0011***	0.0009***	0.0012***
		(0.0003)	(0.0002)	(0.0003)	(0.0003)
Multi		0.0024***	0.0024***	0.0024***	0.0024***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
SOE share		-0.0040***	-0.0040***		
		(0.0011)	(0.0011)		
FIE share		0.0006	0.0006		
		(0.0007)	(0.0007)		
EXP share		-0.0005	-0.0005		
		(0.0008)	(0.0008)		
R&D share		0.0010	0.0009		
		(0.0038)	(0.0038)		
SOE dummy				-0.0031***	-0.0031***
				(0.0010)	(0.0010)
FIE dummy				0.0002	0.0002
				(0.0006)	(0.0006)
EXP dummy				-0.0005	-0.0005
				(0.0006)	(0.0006)
R&D dummy				-0.0008	-0.0008
				(0.0005)	(0.0005)
		Industry-level controls			
TFP^N		0.0033		0.0032	
		(0.0113)		(0.0113)	
Log(Labour productivity)^N			0.0047		0.0049
			(0.0120)		(0.0120)
Log(KL ratio)^N		0.0080	0.0048	0.0047	0.0014
		(0.0166)	(0.0178)	(0.0173)	(0.0189)
Log(Size)^N		-0.0284**	-0.0259	-0.0241	-0.0215
		(0.0134)	(0.0138)	(0.0138)	(0.0147)
SOE share^N		0.0914	0.0909		
		(0.0574)	(0.0573)		
FIE share^N		0.1215**	0.1211**		
		(0.0477)	(0.0478)		
EXP share^N		0.0072	0.0070		
		(0.0429)	(0.0428)		
R&D share^N		0.0623	0.0619		
		(0.1636)	(0.1638)		
SOE dummy^N				0.0783	0.0779
				(0.0524)	(0.0524)
FIE dummy^N				0.1018**	0.1015**
				(0.0408)	(0.0408)
EXP dummy^N				-0.0007	-0.0010
				(0.0270)	(0.0270)
R&D dummy^N				-0.0189	-0.0188
				(0.0263)	(0.0263)
CR		-0.0010	-0.0009	-0.0023	-0.0023
		(0.0158)	(0.0158)	(0.0158)	(0.0158)
EI		0.0363	0.0383	0.0396	0.0419
		(0.0443)	(0.0451)	(0.0450)	(0.0459)
Constant	0.0446***	0.1972**	0.1888**	0.1820**	0.1723
	(0.0090)	(0.0909)	(0.0952)	(0.0925)	(0.0971)
Observations	457,022	451,198	451,198	451,198	451,198
Adjusted R-squared	0.0140	0.0149	0.0149	0.0149	0.0149
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
No. of clusters	9,325	9,249	9,249	9,249	9,249

Note: Standard errors clustered at province-industry level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications.

Table 3.9 Effect of industrial electricity price on switching to a less energy intensive industry (2SLS)

VARIABLES	(1) Switch_HL	(2) Switch_HL	(3) Switch_HL	(4) Switch_HL	(5) Switch_HL
Log(IEP)	0.1415	0.2344***	0.2341***	0.2422***	0.2419***
	(0.0740)	(0.0790)	(0.0790)	(0.0803)	(0.0802)
Log(IEP) × EI		-0.2121	-0.2121	-0.2171	-0.2170
		(0.1464)	(0.1464)	(0.1462)	(0.1462)
		Firm-level controls			
TFP		0.0005**		0.0005**	
		(0.0002)		(0.0002)	
Log(Labour productivity)			0.0005**		0.0005**
			(0.0002)		(0.0002)
Log(KL ratio)		-0.0012***	-0.0016***	-0.0012***	-0.0016***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(Size)		0.0010***	0.0014***	0.0010***	0.0014***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Multi		0.0031***	0.0031***	0.0031***	0.0030***
		(0.0005)	(0.0005)	(0.0005)	(0.0005)
SOE share		-0.0028**	-0.0029**		
		(0.0012)	(0.0012)		
FIE share		0.0004	0.0004		
		(0.0006)	(0.0006)		
EXP share		0.0022***	0.0022***		
		(0.0006)	(0.0006)		
R&D share		-0.0094***	-0.0094***		
		(0.0032)	(0.0032)		
SOE dummy				-0.0028**	-0.0028**
				(0.0011)	(0.0011)
FIE dummy				-0.0002	-0.0002
				(0.0006)	(0.0006)
EXP dummy				0.0013**	0.0013**
				(0.0005)	(0.0005)
R&D dummy				0.0000	0.0000
				(0.0004)	(0.0004)
		Industry-level controls			
TFP^N		-0.0034		-0.0052	
		(0.0079)		(0.0078)	
Log(Labour productivity)^N			-0.0027		-0.0039
			(0.0082)		(0.0081)
Log(KL ratio)^N		0.0046	0.0070	-0.0033	0.0003
		(0.0122)	(0.0124)	(0.0127)	(0.0128)
Log(Size)^N		-0.0231**	-0.0252**	-0.0157	-0.0188
		(0.0109)	(0.0109)	(0.0112)	(0.0112)
SOE share^N		-0.1450***	-0.1446***		
		(0.0558)	(0.0557)		
FIE share^N		-0.0684	-0.0685		
		(0.0377)	(0.0377)		
EXP share^N		-0.0076	-0.0075		
		(0.0253)	(0.0253)		
R&D share^N		0.3827**	0.3843***		
		(0.1487)	(0.1482)		
SOE dummy^N				-0.1152**	-0.1144**
				(0.0529)	(0.0528)
FIE dummy^N				-0.0372	-0.0372
				(0.0324)	(0.0324)
EXP dummy^N				-0.0317	-0.0317
				(0.0201)	(0.0201)
R&D dummy^N				-0.0180	-0.0181
				(0.0174)	(0.0174)
CR		-0.0003	-0.0002	-0.0002	-0.0000
		(0.0127)	(0.0127)	(0.0127)	(0.0127)
EI		-0.0857	-0.0849	-0.0865	-0.0849
		(0.0897)	(0.0894)	(0.0895)	(0.0893)
Constant	0.0616	0.2973***	0.2951***	0.2920***	0.2872***
	(0.0347)	(0.0756)	(0.0783)	(0.0756)	(0.0782)
Observations	457,022	451,198	451,198	451,198	451,198
Adjusted R-squared	0.0157	0.0162	0.0162	0.0161	0.0161
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Underidentification (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Weakidentification (F statistic)	8,757	4,383	4,393	4,239	4,247
No. of clusters	256,053	255,832	255,832	255,832	255,832

Note: Standard errors clustered at firm level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications. Instrument tests include the under-identification test (Kleibergen-Paap rk LM statistic) and weak-identification test (Kleibergen-Paap Wald rk F statistic). The null hypothesis is that the matrix is not full column rank, a rejection of the null indicates that the model is identified. Null hypothesis for weak-identification test shows that the excluded instruments are correlated with the endogenous regressor but only weakly. Large F statistic that exceeds the Stock-Yogo critical values eliminates the weak identification concern.

Table 3.10 Effect of industrial electricity price on switching to a more energy intensive industry (2SLS)

VARIABLES	(1) Switch_LH	(2) Switch_LH	(3) Switch_LH	(4) Switch_LH	(5) Switch_LH
Log(IEP)	-0.2782***	-0.2235***	-0.2239***	-0.2117***	-0.2122***
	(0.0720)	(0.0732)	(0.0731)	(0.0744)	(0.0743)
Log(IEP) × EI		-0.2414***	-0.2413***	-0.2393***	-0.2391***
		(0.0822)	(0.0822)	(0.0820)	(0.0820)
		Firm-level controls			
TFP		0.0004		0.0004**	
		(0.0002)		(0.0002)	
Log(Labour productivity)			0.0004		0.0004
			(0.0002)		(0.0002)
Log(KL ratio)		0.0005	0.0002	0.0005	0.0001
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log(Size)		0.0007***	0.0010***	0.0008***	0.0011***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Multi		0.0024***	0.0024***	0.0024***	0.0024***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
SOE share		-0.0040***	-0.0041***		
		(0.0011)	(0.0011)		
FIE share		0.0006	0.0006		
		(0.0006)	(0.0006)		
EXP share		-0.0006	-0.0006		
		(0.0006)	(0.0006)		
R&D share		0.0017	0.0017		
		(0.0037)	(0.0037)		
SOE dummy				-0.0032***	-0.0032***
				(0.0010)	(0.0010)
FIE dummy				0.0002	0.0002
				(0.0006)	(0.0006)
EXP dummy				-0.0005	-0.0005
				(0.0005)	(0.0005)
R&D dummy				-0.0006	-0.0006
				(0.0004)	(0.0004)
		Industry-level controls			
TFP^N		0.0040		0.0043	
		(0.0078)		(0.0078)	
Log(Labour productivity)^N			0.0048		0.0053
			(0.0079)		(0.0080)
Log(KL ratio)^N		0.0191	0.0156	0.0168	0.0129
		(0.0113)	(0.0112)	(0.0115)	(0.0114)
Log(Size)^N		-0.0383***	-0.0355***	-0.0352***	-0.0321***
		(0.0102)	(0.0100)	(0.0103)	(0.0101)
SOE share^N		0.1128**	0.1122**		
		(0.0456)	(0.0456)		
FIE share^N		0.1586***	0.1584***		
		(0.0375)	(0.0375)		
EXP share^N		-0.0105	-0.0108		
		(0.0260)	(0.0260)		
R&D share^N		0.0313	0.0301		
		(0.1220)	(0.1220)		
SOE dummy^N				0.0965**	0.0960**
				(0.0423)	(0.0422)
FIE dummy^N				0.1195***	0.1193***
				(0.0322)	(0.0322)
EXP dummy^N				-0.0050	-0.0052
				(0.0186)	(0.0186)
R&D dummy^N				-0.0089	-0.0088
				(0.0165)	(0.0165)
CR		-0.0001	-0.0001	-0.0016	-0.0016
		(0.0122)	(0.0122)	(0.0122)	(0.0122)
EI		-0.1162**	-0.1151**	-0.1142**	-0.1127**
		(0.0476)	(0.0476)	(0.0478)	(0.0478)
Constant	-0.1287***	0.0798	0.0744	0.0717	0.0648
	(0.0338)	(0.0731)	(0.0747)	(0.0736)	(0.0749)
Observations	457,022	451,198	451,198	451,198	451,198
Adjusted R-squared	0.0116	0.0128	0.0128	0.0129	0.0129
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes
Underidentification (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Weakidentification (F statistic)	8,757	4,383	4,393	4,239	4,247
No. of clusters	256,053	255,832	255,832	255,832	255,832

Note: Standard errors clustered at firm level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications. Instrument tests include the under-identification test (Kleibergen-Paap rk LM statistic) and weak-identification test (Kleibergen-Paap Wald rk F statistic). The null hypothesis is that the matrix is not full column rank, a rejection of the null indicates that the model is identified. Null hypothesis for weak-identification test shows that the excluded instruments are correlated with the endogenous regressor but only weakly. Large F statistic that exceeds the Stock-Yogo critical values eliminates the weak identification concern.

Table 3.11 Effect of industrial electricity price on EI gap (Pooled OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Switch to a less energy intensive industry			*Switch to a more energy intensive industry*		
Log(IEP)	0.4245***	0.4048***	0.4040***	0.3456***	0.3433***	0.3435***
	(0.0622)	(0.0636)	(0.0636)	(0.0470)	(0.0482)	(0.0482)
Log(IEP) × EI		0.1199	0.1226		0.1959**	0.1959**
		(0.2689)	(0.2689)		(0.0947)	(0.0947)
		Industry-level controls				
TFP		0.0048***			0.0027**	
		(0.0014)			(0.0011)	
Log(Labour productivity)			0.0042***			0.0026**
			(0.0014)			(0.0011)
Log(KL ratio)		-0.0049***	-0.0085***		0.0038***	0.0017
		(0.0016)	(0.0016)		(0.0013)	(0.0013)
Log(Size)		0.0034**	0.0064***		0.0036***	0.0053***
		(0.0014)	(0.0013)		(0.0012)	(0.0010)
Multi		0.0171***	0.0171***		0.0105***	0.0105***
		(0.0026)	(0.0026)		(0.0020)	(0.0020)
SOE dummy		-0.0126	-0.0128		-0.0125**	-0.0125**
		(0.0067)	(0.0067)		(0.0050)	(0.0050)
FIE dummy		0.0025	0.0024		-0.0025	-0.0025
		(0.0033)	(0.0033)		(0.0026)	(0.0026)
EXP dummy		0.0061**	0.0061**		-0.0032	-0.0032
		(0.0028)	(0.0028)		(0.0023)	(0.0023)
R&D dummy		-0.0006	-0.0006		-0.0028	-0.0028
		(0.0025)	(0.0025)		(0.0020)	(0.0020)
		Industry-level controls				
TFP^N		-0.0416			0.0241	
		(0.0454)			(0.0392)	
Log(Labour productivity)^N			-0.0360			0.0234
			(0.0480)			(0.0399)
Log(KL ratio)^N		0.0682	0.0989		-0.0440	-0.0629
		(0.0734)	(0.0760)		(0.0537)	(0.0540)
Log(Size)^N		-0.1819***	-0.2077***		-0.0492	-0.0335
		(0.0673)	(0.0681)		(0.0470)	(0.0479)
SOE dummy^N		-0.6778**	-0.6719**		0.4804**	0.4766**
		(0.3178)	(0.3171)		(0.1961)	(0.1961)
FIE dummy^N		-0.0156	-0.0155		0.3016	0.3012
		(0.1769)	(0.1770)		(0.1591)	(0.1590)
EXP dummy^N		-0.1803	-0.1796		-0.0192	-0.0199
		(0.1172)	(0.1170)		(0.0907)	(0.0907)
R&D dummy^N		0.0171	0.0167		-0.1587**	-0.1584**
		(0.1015)	(0.1015)		(0.0780)	(0.0780)
CR		-0.0823	-0.0815		0.0283	0.0279
		(0.0736)	(0.0736)		(0.0600)	(0.0599)
EI		0.4740	0.4628		-1.7003***	-1.7011***
		(1.7312)	(1.7324)		(0.6183)	(0.6193)
Constant	-2.7511***	-1.1421	-1.1532	-2.2235***	-1.8538***	-1.8584***
	(0.4004)	(0.6061)	(0.6236)	(0.3031)	(0.4713)	(0.4796)
Observations	451,876	446,052	446,052	449,133	443,309	443,309
Adjusted R-squared	0.0194	0.0204	0.0204	0.0120	0.0129	0.0129
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of clusters	255,266	252,990	252,990	254,889	251,120	251,120

Note: Standard errors clustered at firm level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications.

Table 3.12 Effect of industrial electricity price on EI gap (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Switch to a less energy intensive industry*			*Switch to a more energy intensive industry*		
Log(IEP)	0.5924	1.1054**	1.1028**	-1.5561***	-1.1770***	-1.1771***
	(0.4266)	(0.4304)	(0.4806)	(0.3329)	(0.3471)	(0.3467)
Log(IEP) × EI		-0.9216	-0.9205		-1.1993***	-1.1987***
		(1.0577)	(1.0577)		(0.4056)	(0.4056)
Firm-level controls						
TFP		0.0050***			0.0026**	
		(0.0014)			(0.0011)	
Log(Labour productivity)			0.0044***			0.0025**
			(0.0014)			(0.0011)
Log(KL ratio)		-0.0047***	-0.0085***		0.0044***	0.0024
		(0.0017)	(0.0016)		(0.0013)	(0.0013)
Log(Size)		0.0032**	0.0064***		0.0032***	0.0049***
		(0.0014)	(0.0013)		(0.0012)	(0.0010)
Multi		0.0173***	0.0173***		0.0105***	0.0105***
		(0.0026)	(0.0026)		(0.0020)	(0.0020)
SOE dummy		-0.0125	-0.0127		-0.0128**	-0.0129***
		(0.0067)	(0.0067)		(0.0050)	(0.0050)
FIE dummy		0.0020	0.0020		-0.0025	-0.0025
		(0.0033)	(0.0033)		(0.0026)	(0.0026)
EXP dummy		0.0058**	0.0059**		-0.0033	-0.0033
		(0.0029)	(0.0029)		(0.0023)	(0.0023)
R&D dummy		-0.0008	-0.0008		-0.0019	-0.0019
		(0.0025)	(0.0025)		(0.0020)	(0.0020)
Industry-level controls						
TFP^N		-0.0479			0.0300	
		(0.0457)			(0.0393)	
Log(Labour productivity)^N			-0.0392			0.0259
			(0.0480)			(0.0399)
Log(KL ratio)^N		0.0496	0.0840		0.0171	-0.0050
		(0.0761)	(0.0777)		(0.0560)	(0.0560)
Log(Size)^N		-0.1600**	-0.1891***		-0.1054**	-0.0868
		(0.0701)	(0.0701)		(0.0493)	(0.0498)
SOE dummy^N		-0.7420**	-0.7350**		0.5767***	0.5719***
		(0.3184)	(0.3176)		(0.1964)	(0.1963)
FIE dummy^N		-0.0421	-0.0421		0.3885**	0.3884**
		(0.1793)	(0.1794)		(0.1609)	(0.1609)
EXP dummy^N		-0.1788	-0.1783		-0.0379	-0.0386
		(0.1172)	(0.1171)		(0.0907)	(0.0908)
R&D dummy^N		0.0048	0.0045		-0.1083	-0.1080
		(0.1023)	(0.1024)		(0.0785)	(0.0785)
CR		-0.0914	-0.0903		0.0332	0.0325
		(0.0739)	(0.0739)		(0.0601)	(0.0601)
EI		7.1051	7.1089		7.2866***	7.2775***
		(6.7376)	(6.7407)		(2.5944)	(2.5953)
Constant	-3.8324	-5.7005	-5.7144	10.0224***	8.0841***	8.0976***
	(2.7474)	(3.1655)	(3.1717)	(2.1435)	(2.2969)	(2.3015)
Observations	451,876	446,052	446,052	449,133	443,309	443,309
Adjusted R-squared	0.0194	0.0201	0.0201	0.0092	0.0092	0.0107
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Weakidentification (F statistic)	8,703	4,203	4,212	8,647	4,184	4,193
No. of clusters	255,266	252,990	252,990	254,889	251,120	251,120

Note: Standard errors clustered at firm level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications. Instrument tests include the under-identification test (Kleibergen-Paap rk LM statistic) and weak-identification test (Kleibergen-Paap Wald rk F statistic). The null hypothesis is that the matrix is not full column rank, a rejection of the null indicates that the model is identified. Null hypothesis for weak-identification test shows that the excluded instruments are correlated with the endogenous regressor but only weakly. Large F statistic that exceeds the Stock-Yogo critical values eliminates the weak identification concern.

Table 3.13 Effect of industrial electricity price on switching with the subsample (Pooled OLS)

VARIABLES	(1) Switch_HL	(2) Switch_HL	(3) Switch_HL	(4) Switch_LH	(5) Switch_LH	(6) Switch_LH
Log(IEP)	0.0739***	0.0781***	0.0780***	0.0892***	0.0856***	0.0857***
	(0.0181)	(0.0184)	(0.0184)	(0.0186)	(0.0195)	(0.0195)
Log(IEP) × EI		-0.0437	-0.0434		0.0687**	0.0687**
		(0.0625)	(0.0625)		(0.0348)	(0.0348)
		Firm-level controls				
TFP		0.0003			0.0004	
		(0.0003)			(0.0003)	
Log(Labour productivity)			0.0003			0.0003
			(0.0003)			(0.0003)
Log(KL ratio)		-0.0009**	-0.0012***		0.0004	0.0001
		(0.0004)	(0.0004)		(0.0003)	(0.0004)
Log(Size)		0.0008**	0.0010***		0.0006**	0.0009***
		(0.0003)	(0.0003)		(0.0003)	(0.0003)
Multi		0.0031***	0.0031***		0.0022***	0.0022***
		(0.0005)	(0.0005)		(0.0005)	(0.0005)
FIE dummy		-0.0001	-0.0001		0.0002	0.0002
		(0.0006)	(0.0006)		(0.0007)	(0.0007)
EXP dummy		0.0016***	0.0016***		-0.0002	-0.0002
		(0.0006)	(0.0006)		(0.0006)	(0.0006)
R&D dummy		0.0001	0.0001		-0.0007	-0.0007
		(0.0005)	(0.0005)		(0.0005)	(0.0005)
		Industry-level controls				
TFP^N		-0.0111			0.0107	
		(0.0126)			(0.0116)	
Log(Labour productivity)^N			-0.0108			0.0144
			(0.0128)			(0.0124)
Log(KL ratio)^N		-0.0175	-0.0088		-0.0005	-0.0107
		(0.0190)	(0.0186)		(0.0179)	(0.0202)
Log(Size)^N		0.0024	-0.0048		-0.0150	-0.0069
		(0.0153)	(0.0159)		(0.0145)	(0.0159)
SOE dummy^N		-0.1061	-0.1047		0.1505**	0.1495**
		(0.0825)	(0.0824)		(0.0609)	(0.0609)
FIE dummy^N		-0.0221	-0.0219		0.0872**	0.0865**
		(0.0406)	(0.0406)		(0.0415)	(0.0415)
EXP dummy^N		-0.0292	-0.0289		0.0026	0.0021
		(0.0291)	(0.0291)		(0.0281)	(0.0281)
R&D dummy^N		-0.0227	-0.0228		-0.0294	-0.0293
		(0.0229)	(0.0229)		(0.0284)	(0.0283)
CR		-0.0018	-0.0016		-0.0017	-0.0018
		(0.0175)	(0.0175)		(0.0159)	(0.0159)
EI		0.0071	0.0075		0.0354	0.0401
		(0.0692)	(0.0692)		(0.0486)	(0.0495)
Constant	0.0310***	0.1686	0.1703	0.0434***	0.0794	0.0572
	(0.0087)	(0.1121)	(0.1174)	(0.0092)	(0.0977)	(0.1027)
Observations	402,229	397,255	397,255	402,229	397,255	397,255
Adjusted R-squared	0.0161	0.0168	0.0168	0.0137	0.0144	0.0144
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of clusters	8,910	8,837	8,837	8,910	8,837	8,837

Note: Standard errors clustered at province-industry level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications. The subsample excludes all SOEs and top 10% largest firms.

Table 3.14 Effect of industrial electricity price on switching with the subsample (2SLS)

VARIABLES	(1) Switch_HL	(2) Switch_HL	(3) Switch_HL	(4) Switch_LH	(5) Switch_LH	(6) Switch_LH
Log(IEP)	0.1199	0.2135**	0.2133**	-0.3489***	-0.2570***	-0.2583***
	(0.0758)	(0.0829)	(0.0828)	(0.0740)	(0.0764)	(0.0763)
Log(IEP) × EI		-0.1689	-0.1689		-0.3244***	-0.3243***
		(0.1744)	(0.1744)		(0.0970)	(0.0970)
Firm-level controls						
TFP		0.0004			0.0003	
		(0.0002)			(0.0002)	
Log(Labour productivity)			0.0003			0.0003
			(0.0002)			(0.0002)
Log(KL ratio)		-0.0009***	-0.0012***		0.0006	0.0003
		(0.0003)	(0.0003)		(0.0003)	(0.0003)
Log(Size)		0.0008***	0.0010***		0.0005**	0.0007***
		(0.0003)	(0.0003)		(0.0003)	(0.0002)
Multi		0.0032***	0.0032***		0.0022***	0.0022***
		(0.0005)	(0.0005)		(0.0005)	(0.0005)
FIE dummy		-0.0002	-0.0002		0.0002	0.0002
		(0.0006)	(0.0006)		(0.0006)	(0.0006)
EXP dummy		0.0016***	0.0016***		-0.0003	-0.0003
		(0.0005)	(0.0005)		(0.0005)	(0.0005)
R&D dummy		0.0001	0.0001		-0.0005	-0.0005
		(0.0005)	(0.0005)		(0.0004)	(0.0004)
Industry-level controls						
TFP^N		-0.0119			0.0113	
		(0.0083)			(0.0083)	
Log(Labour productivity)^N			-0.0112			0.0143
			(0.0085)			(0.0084)
Log(KL ratio)^N		-0.0217	-0.0125		0.0140	0.0036
		(0.0129)	(0.0130)		(0.0121)	(0.0120)
Log(Size)^N		0.0070	-0.0006		-0.0285***	-0.0203
		(0.0116)	(0.0117)		(0.0110)	(0.0109)
SOE dummy^N		-0.1186	-0.1170		0.1734***	0.1724***
		(0.0611)	(0.0609)		(0.0497)	(0.0497)
FIE dummy^N		-0.0284	-0.0283		0.1089***	0.1084***
		(0.0333)	(0.0333)		(0.0340)	(0.0340)
EXP dummy^N		-0.0286	-0.0283		-0.0025	-0.0030
		(0.0211)	(0.0211)		(0.0196)	(0.0196)
R&D dummy^N		-0.0255	-0.0256		-0.0176	-0.0175
		(0.0178)	(0.0178)		(0.0174)	(0.0174)
CR		-0.0033	-0.0031		-0.0005	-0.0006
		(0.0133)	(0.0133)		(0.0128)	(0.0128)
EI		-0.0628	-0.0620		-0.1451***	-0.1411**
		(0.1034)	(0.1031)		(0.0550)	(0.0549)
Constant	0.0525	0.2191***	0.2185***	-0.1618***	-0.0392	-0.0585
	(0.0355)	(0.0805)	(0.0830)	(0.0347)	(0.0778)	(0.0792)
Observations	402,229	397,255	397,255	402,229	397,255	397,255
Adjusted R-squared	0.0160	0.0165	0.0165	0.0102	0.0116	0.0116
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Weakidentification (F statistic)	7,754	3,767	3,776	7,754	3,767	3,776
No. of clusters	229,674	229,384	229,384	229,674	229,384	229,384

Note: Standard errors clustered at firm level are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications. Instrument tests include the under-identification test (Kleibergen-Paap rk LM statistic) and weak-identification test (Kleibergen-Paap Wald rk F statistic). The null hypothesis is that the matrix is not full column rank, a rejection of the null indicates that the model is identified. Null hypothesis for weak-identification test shows that the excluded instruments are correlated with the endogenous regressor but only weakly. Large F statistic that exceeds the Stock-Yogo critical values eliminates the weak identification concern. The subsample excludes all SOEs and top 10% largest firms.

Appendix B

Table B.1 Independent variable definition

Variable	Definition	Source
Firm-level		
TFP	Total factor productivity (LP method)	Chinese Industrial Enterprises Dataset
Labour productivity	Real value added per worker, million yuan/1000 person in 2005 price	Chinese Industrial Enterprises Dataset
KL ratio	Real fixed assets per worker, million yuan/1000 person in 2005 price	Chinese Industrial Enterprises Dataset
Size	Total fixed asset stock, 10,000 yuan in 2005 price	Chinese Industrial Enterprises Dataset
SOE share	State-owned capital/Total capital	Chinese Industrial Enterprises Dataset
FIE share	Foreign, Hong Kong, Macao and Taiwan capital/Total capital	Chinese Industrial Enterprises Dataset
EXP share	Export value/Total output	Chinese Industrial Enterprises Dataset
R&D share	Expenditure in research and development/Total output	Chinese Industrial Enterprises Dataset
SOE dummy	=1 if SOE share >51%	Chinese Industrial Enterprises Dataset
FIE dummy	=1 if FIE share >51%	Chinese Industrial Enterprises Dataset
EXP dummy	=1 if EXP share >0	Chinese Industrial Enterprises Dataset
R&D dummy	=1 if R&D share >0	Chinese Industrial Enterprises Dataset
Multi	Dummy variable with value one if survey shows a firm produces multiple products (roughly defined at the 3-digit and 4-digit level)	Chinese Industrial Enterprises Dataset
Industry-level		
CR	Output of the top 5% of firms/Output of all firms in that industry	Chinese Industrial Enterprises Dataset
EI	Electricity consumption/Real output	China Energy statistical Yearbooks
Province-level		
IEP	Industrial electricity price, yuan/MWH	China Price Information Center
Coal production	Province-level coal production, 10,000 tons	China Energy statistical Yearbooks
Capacity	Electricity generation from coal to electricity generation from all types of fuel	China Energy statistical Yearbooks

Table B.2 2-digit manufacturing sectors electricity intensity ranking

Manufacturing	CIC	2005	2006	2007	mean
Smelting and processing of non-ferrous metals	33	1856	1414	1330	1533
Manufacture of non-metallic mineral products	31	1544	1429	1193	1389
Manufacture of chemical raw materials and chemical products	26	1302	1193	1037	1177
Smelting and processing of ferrous metals	32	1188	1196	1086	1157
Manufacture of artwork and other manufacturing	42	1354	1112	854.2	1107
Manufacture of rubber	29	952.8	868.5	759.8	860.4
Manufacture of paper and paper prod.	22	979.8	889.3	688.8	852.6
Manufacture of chemical fibers	28	894.1	763.7	672.0	776.6
Manufacture of metal products	34	773.6	710.2	591.5	691.8
Manufacture of textiles	17	649.9	674.0	600.2	641.4
Manufacture of plastics	30	636.2	556.6	469.2	554.0
Processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products	20	577.6	524.2	422.7	508.2
Printing and recorded media	23	420.8	389.9	350.3	387.0
Manufacture of medicines	27	360.5	318.0	268.3	315.6
Manufacture of general purpose machinery	35	324.9	283.4	243.2	283.8
Manufacture of foods	14	303.8	284.6	250.0	279.5
Manufacture of special purpose machinery	36	300.6	260.6	216.4	259.2
Manufacture of articles for culture,education and sport activity	24	287.0	247.0	219.2	251.0
Processing of petroleum, coking,processing of nuclear fuel	25	261.2	235.9	229.5	242.2
Manufacture of beverages	15	247.8	229.4	199.1	225.4
Processing of food from agric. products	13	238.7	228.2	191.4	219.4
Manufacture of textile,apparel, footwear£¬and caps	18	176.1	176.6	163.8	172.2
Manufacture of transport equipment	37	191.4	169.5	153.9	171.6
Manufacture of electrical machinery and equipment	39	176.8	155.4	142.2	158.1
Manufacture of leather, fur, feather and related products	19	158.4	155.2	143.0	152.2
Manufacture of furniture	21	170.1	151.3	122.2	147.9
Manufacture of measuring instruments and machinery for cultural activity and office work	41	152.9	146.4	142.0	147.1
Manufacture of communication equipment, computers and other	40	121.5	121.5	122.3	121.8

Note: Data source China Energy statistical Yearbooks 2006-2008. Unit kWh/10,000 yuan.

Table B.3 Summary of the energy variables by province (2005-2007)

Province	Industrial electricity price (Yuan/MWH)	Thermal power generation capacity	Coal production (10,000 tons)
Guangdong	772.9	0.78	127.8
Jiangsu	721.3	0.98	2782
Jilin	719.2	0.85	3024
Zhejiang	718.6	0.79	24.78
Shanghai	709.5	1	0
Liaoning	690.3	0.95	6704
Anhui	684.4	0.98	8695
Tianjin	676.4	1	0
Heilongjiang	676	0.98	9950
Hebei	668.4	0.99	8556
Shandong	658.6	1	14206
Hubei	656	0.40	1070
Sichuan	646.5	0.36	8761
Beijing	646.2	0.98	732.6
Fujian	608.1	0.65	1935
Jiangxi	604.4	0.81	2782
Guangxi	601.6	0.54	700.8
Chongqing	590.2	0.77	3968
Ningxia	583.8	0.95	3218
Henan	568.3	0.95	19194
Gansu	562.5	0.68	3840
Hunan	529	0.63	5967
Guizhou	520	0.74	11159
Yunnan	504.8	0.50	7185
Shanxi	491	0.98	58863
Innermongolia	444.4	0.98	30268
Average	626.9	0.80	8301

Note: Data source China Energy statistical Yearbooks and China Price Information Center. Thermal power generation capacity is defined as the share of electricity generated by coal over electricity generated by all types of fuels. Shaanxi and Qinghai provinces are dropped as outliers in terms of coal production and industrial electricity price. These two provinces account for approximately 0.94% of total number of firms.

Table B.4 Correlation matrix (obs = 457022)

	IEP	Coal production	Capacity	TFP	Labour productivity	KL ratio	Size	SOE share	FIE share	EXP share	R&D share	SOE dummy	FIE dummy	EXP dummy	R&D dummy	CR	EI
IEP	1																
Coal production	-0.56	1															
Capacity	0.13	0.29	1														
TFP	-0.02	0.1	0.07	1													
Labour productivity	-0.05	0.11	0.1	0.59	1												
KL ratio	-0.03	0.05	0.04	0.12	0.31	1											
Size	-0.03	0.04	0.01	0.29	0.11	0.41	1										
SOE share	-0.1	0.06	-0.02	-0.01	-0.03	0.05	0.1	1									
FIE share	0.23	-0.16	0	0.1	0	0.07	0.08	-0.07	1								
EXP share	0.19	-0.17	-0.05	0.03	-0.13	-0.1	0.01	-0.07	0.41	1							
R&D share	-0.01	-0.01	0.01	-0.01	-0.01	0.06	0.06	0.09	0.02	-0.02	1						
SOE dummy	-0.1	0.06	-0.02	-0.02	-0.03	0.04	0.09	0.97	-0.07	-0.06	0.08	1					
FIE dummy	0.22	-0.15	-0.01	0.09	0	0.07	0.07	-0.07	0.97	0.38	0.02	-0.08	1				
EXP dummy	0.12	-0.1	-0.01	0.12	-0.07	-0.05	0.09	-0.05	0.38	0.8	0	-0.05	0.35	1			
R&D dummy	0.07	-0.11	-0.02	0.12	-0.01	0.11	0.17	0.1	0.14	0.07	0.32	0.09	0.13	0.13	1		
CR	0.05	-0.02	0.05	0.02	0.11	0.07	0.06	0.01	0.01	-0.1	0.04	0.01	0.01	-0.08	0.07	1	
EI	-0.14	0.1	-0.03	-0.03	0.03	0.1	0.08	0.02	-0.11	-0.13	0	0.02	-0.11	-0.12	-0.04	-0.09	1

Table B.5 Effect of industrial electricity price on switching (Probit)

VARIABLES	(1) Switch	(2) Switch	(3) Switch	(4) Switch
Log(IEP)	0.1112***	0.1110***	0.1122***	0.1120***
	(0.0199)	(0.0199)	(0.0199)	(0.0199)
Log(IEP) × EI	0.1787***	0.1801***	0.1749***	0.1763***
	(0.0554)	(0.0554)	(0.0553)	(0.0553)
	Firm-level controls			
TFP	0.0023***		0.0023***	
	(0.0003)		(0.0003)	
Log(Labour productivity)		0.0021***		0.0022***
		(0.0003)		(0.0003)
Log(KL ratio)	-0.0007	-0.0025***	-0.0009**	-0.0027***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Log(Size)	0.0019***	0.0034***	0.0021***	0.0036***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Multi	0.0066***	0.0066***	0.0066***	0.0066***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
SOE ratio	-0.0094***	-0.0094***		
	(0.0018)	(0.0018)		
FIE ratio	0.0026***	0.0026***		
	(0.0009)	(0.0009)		
EXP ratio	0.0028***	0.0028***		
	(0.0011)	(0.0011)		
RD ratio	-0.0044	-0.0046		
	(0.0052)	(0.0052)		
SOE dummy			-0.0083***	-0.0083***
			(0.0017)	(0.0017)
FIE dummy			0.0009	0.0009
			(0.0009)	(0.0009)
EXP dummy			0.0006	0.0006
			(0.0008)	(0.0008)
R&D dummy			-0.0001	-0.0001
			(0.0007)	(0.0007)
	Industry-level controls			
TFP^N	0.0018		0.0024	
	(0.0096)		(0.0096)	
Log(Labour productivity)^N		0.0032		0.0039
		(0.0098)		(0.0098)
Log(KL ratio)^N	0.0155	0.0133	0.0124	0.0097
	(0.0136)	(0.0143)	(0.0136)	(0.0144)
Log(Size)^N	-0.0367***	-0.0351***	-0.0341***	-0.0322**
	(0.0130)	(0.0129)	(0.0130)	(0.0129)
SOE ratio^N	0.0609	0.0611		
	(0.0593)	(0.0592)		
FIE ratio^N	0.0289	0.0285		
	(0.0456)	(0.0456)		
EXP ratio^N	-0.0042	-0.0043		
	(0.0347)	(0.0347)		
R&D ratio^N	0.0035	0.0035		
	(0.0029)	(0.0029)		
SOE dummy^N			0.0750	0.0751
			(0.0563)	(0.0562)
FIE dummy^N			0.0314	0.0310
			(0.0405)	(0.0405)
EXP dummy^N			-0.0122	-0.0125
			(0.0261)	(0.0262)
RD dummy^N			-0.0094	-0.0094
			(0.0220)	(0.0220)
CR	-0.0014	-0.0015	-0.0022	-0.0023
	(0.0169)	(0.0169)	(0.0169)	(0.0169)
EI	-1.0858***	-1.0925***	-1.0592***	-1.0656***
	(0.3573)	(0.3574)	(0.3567)	(0.3569)
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Observations	450,764	450,764	450,764	450,764

Note: Robust standard errors are reported in parentheses. Siginificant at **5%, ***1%. All monetary values are deflated to 2005 prices via provincial CPI. Year, province and 4-digit industry dummies are included in all specifications.

Chapter 4

Shell Shocked: The Impact of Foreign Entry on the Gasoline Retail Market in China

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By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Shell Shocked: The Impact of Foreign Entry on the Gasoline Retail Market in China

Abstract

Since joining the WTO in 2001 restrictions on foreign entry into China's energy sector have been steadily reduced. We investigate the impact of Royal Dutch Shell's entry on the pricing behavior of three varieties of gasoline in the retail and wholesale markets. Using a pairwise approach and difference-in-difference method we show that a year after entry, the average absolute price differential of gasoline between any two pair of cities increased by around 1.4 percent, before falling the following year. In other words, Shell's entry causes a price divergence in a certain period of time. Larger effects were found for highly refined fuels in Western cities. Wholesale prices follow a similar pattern. Policy implications are discussed.

JEL: L130, L810, E310

Keywords: Royal Dutch Shell, Competition, Prices, Gasoline, Energy

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4.1 Introduction

As one of the most rapidly growing consumer markets in the world, China has received considerable attention from multinational retailers. China's retail sales in 2014 reached 23.45 trillion RMB (US3.78 trillion in 2015 prices), 12.2 percent higher than the previous year (National Bureau of Statistics of China 2014). Hence, China's growing consumer market presents an enormous opportunity for domestic and foreign firms. One particular difficulty faced by foreign firms is the lack of market access to certain sectors which have been subject to strict government regulation on the degree to which foreign investment is permitted. These restrictions were particularly prevalent in the retail gasoline sector which is considered to be one of the most profitable sectors in China. As the world's second largest oil consumer, and since 2010 the world's largest energy consumer, China's demand for conventional gasoline has grown rapidly and is predicted to continue to grow further as automobile ownership expands.[1]

Prior to China's entry into the World Trade Organization (WTO) very little foreign investment was permitted in the energy sector. However, following a series of concessions agreed by China as part of the WTO negotiations, entry barriers in the gasoline retail sector have gradually been eliminated. China's new stance on the energy sector is based on the premise that the economy and consumers would benefit from greater market-oriented competition, enhanced brand awareness and improvements in non-fuel service quality. The most significant policy change came in December 2004 when the *Measures for the Administration on Foreign Investment in Commercial Sector* was issued by the Ministry of Commerce. This new ruling permitted, for the first time, foreign-funded retail enterprises to establish gasoline retail service stations and allowed foreign firms to buy and sell refined oil without geographical

[1]Recent data shows that the motor vehicles, motorcycles, fuel and auto parts sectors account for 30% of China's total retail assets and 13% and 20% of physical retail enterprises and employment, respectively (Third National Economic Census 2014).

restrictions (Ministry of Commerce, PR China). The 2004 deregulation was followed in December 2006 by a similar measure that opened up the wholesale market for refined oil to foreign firms after which China's energy market was considered to be fully open.

The contribution of this paper is to be one of the first to examine the impact of China's open market policy on the retail gasoline and wholesale gasoline markets. Our research follows in the tradition of Basker (2005) who examines Wal-Mart's entry into local markets on local prices in the US and Holmes et al. (2013) who investigate the determinants of gasoline price integration in the US. More specifically, we provide an insight into how the entry of a large multinational company, in this case Royal Dutch Shell (hereafter Shell), affected retail and wholesale energy prices and the pattern of energy price convergence within China. In this paper we investigate two potential mechanisms by which foreign entry has an impact on gasoline market in China. The first channel is a local or market-specific mechanism that works though retail competition at the local market level. The average price level tends to decrease at the beginning due to the undercutting initiating by new entrants to steal market share. When margins get too low and the allocation of market tends to be settled down, the average price rebounds significantly. The second channel, which we call the aggregation mechanism, works through upstream interactions with domestic incumbents in the wholesale market and which in turn may affect the wholesale price of fuel across the whole of China.

Our data are derived from the combination of two unique datasets. The first is the location and opening year of China's Shell branded service stations opened either by Shell alone or as part of a joint venture. Over the last ten years Shell has managed to develop a network of more than 1,100 service stations across 48 cities covering the northern, southern, central and southeastern areas of China. The scale of Shell's activity coupled with their early entry into China makes their experience an interesting quasi-experiment by which to investigate various aspects of energy price dynamics in China. The second is a dataset of service station-level fuel prices for 2001 to 2012 from the China Price Monitoring Centre (CPMC) which is a branch of the National Development and Reform Commission (NDRC). To take into account heterogeneity in the quality across varieties of fuel we consider three different grades of gasoline: super premium (Gas#97); premium (Gas#93); and standard (Gas#90).[2]

Our methodological approach is to combine a pairwise approach with the difference-in-differences (DID) method to identify the causal relationship between Shell's entry into a local market and the subsequent effect on absolute price differentials. Following Pesaran et al. (2009) and Holmes et al. (2013) we first calculate the absolute price differentials between gasoline prices for any two cities which have similar propensities to be populated by Shell in a year. We then adopt the DID method and compare the absolute price differentials between two cities where one city has experienced the entry of Shell (the treated) to the absolute price differentials between two cities where neither has a Shell station (the control), and compare the price differentials before and after the entry year. Besides Shell's entry, we also account for the impacts of distance between cities and economic and demographic factors. Considering the differentials of macroeconomic data helps to alleviate concerns of endogeneity as the entry decision of international retailers is unlikely to be based on the economic development gap between any two cities. The pairwise approach is newly developed and commonly used in studies that investigate price behaviour (see e.g. Pesaran et al., 2009; Yazgan and Yilmazkuday, 2011; Holmes et al., 2011, 2013). Through taking the differentials of gasoline prices between any two pairs of cities, the pairwise approach is reasonably robust to cross-section dependence (Pesaran et al., 2009). For example, since within our time period there was considerable energy market deregulation leading to a decentralization of prices, taking differences enables us to eliminate the impact of common shocks that effected all cities in the same year. In addition, taking the difference between any two cities, instead of the difference with group mean or a baseline city, enables us to

[2]Descriptions of each gasoline type are provided in the data section of the paper.

avoid any undesirable shocks from a specific year or the baseline city. Finally, the pairwise approach allows us to also investigate the impact of distance on price dispersion.

To briefly summarize our results, we find that Shell's entry into China's retail gasoline market had a statistically significant effect on gasoline prices across China. Specifically, our results suggest that the entry of Shell into a city increased the average dispersion of prices in China between 1.3 and 1.5 percent in the year of entry although, crucially this positive impact disappears over time. Of the three different fuel types, we find a larger effect for super premium gasoline (Gas#97), that historically had higher profit margins than regular gasoline prices both locally and nationally. For all fuel types we found that the greatest absolute price effect was found in China's less developed western cities which, due to limited competition in the past, would have been exposed to greater competitive pressures following Shell' entry, certainly compared to the already relatively more mature markets in eastern cities. To explain the rise in dispersion we then look at how Shell entry impacts prices and we find that the local retail price for Gas#93 and Gas#97 fell by between 4.2 to 5.0 percent immediately after Shell's entry before increasing by between 2.4 to 3.2 percent in the second year after entry. In terms of the wholesale market, we find that by cooperating with domestic partners, Shell managed to achieve end-to-end integration of the value chain from upstream refineries to downstream retail networks leading to a reduction in overall wholesale prices across China.

The remainder of the paper is organized as follows. Section 4.2 provides a review of the literature. Section 4.3 describes the data and presents some descriptive evidence of the pattern of price dispersion in China. Our empirical approach is presented in Section 4.4 and our empirical results are provided in Section 4.5. Section 4.6 investigates the potential mechanisms that are driving the entry effect and Section 4.7 presents the results from a series of robustness checks. The final section concludes.

4.2 Literature Review

The last thirty years has seen a growth in research examining price dispersion among related products or customers with different preferences. We present in this section studies examining the price effect of the entry of multinational retailers. Significant price reductions are observed at the local level due to the entry of multinational retailers. We also summarize the literature that specifically study the gasoline market and price dispersion. Gasoline price dispersion can be caused by differences in market structure and market conduct, as well as the emergence of vertical integrated refiners. Furthermore, a saw-toothed gasoline pricing pattern named Edgeworth price cycle is investigated in the literature. Overall, studies of the gasoline market are limited and have tended to focus on developed countries.

The review of literature begins with the investigation of persisting price differences. In a monopolistic competition setting, assuming firms can distinguish between customers, firms will price discriminate based on demand elasticities with the result that monopolistically set prices tend to be higher than those under perfect competition. As a result, firms with pricing power set prices above marginal costs. In an imperfectly competitive setting, prices should gradually converge as the entry of new firms leads to greater competition. With new entry (and no exit), price differences should disappear and the average market price should return to the marginal cost level. This brief literature review discusses the various mechanisms by which Shell's entry into China could affect absolute price levels for gasoline in both the retail and wholesale markets and levels of price dispersion within and across cities.

There are numerous explanations why price dispersion can persist across firms within an industry. One sector that has been analyzed in detail is the airline industry. For example, Borenstein and Rose (1994) examined the US airline industry in 1986 and surprisingly found evidence of a positive relationship between price dispersion and competition. They highlighted two main sources of price differences. The first is that variation in prices is driven by the cost-base of firms (airlines serving different passengers in different locations could have a different cost base depending on where the airline is geographically located). Second, prices could differ due to price discrimination usually as a result of differences in market structure, consumer preferences and product characteristics. More recently and in line with traditional microeconomic theory, a second study of the US airline industry by Gerardi and Shapiro (2009) that coincided with the entry of the low-cost carriers finds a significant negative relationship between competition and price differences.[3]

A smaller body of research examines the competition effect of the entry of multinational retailers into local markets including Chen (2003), Basker (2005),Dukes et al. (2006), Hausman and Leibtag (2007), Gielens et al. (2008). As one of the largest players in international retailing, Wal-Mart often serves as a case study. For example, Basker (2005) studies the entry effect of Wal-Mart by combining quarterly price data for a series of commonly bought products after the opening of Wal-Mart stores across the US and finds that after a store is opened there are significant price reductions for several daily consumables such as toothpaste and shampoo. The magnitude of the reduction tended to be in the range of 1.5 to 3 percent in the short term and up to four times higher in the long run. Drawing upon studies on the Wal-Mart effect, two mechanisms are highlighted. First, Wal-Mart's highly efficient supply chain reduces operating costs with Walmart's superior logistics, infrastructure and distribution networks regarded as important components of their retail strategy. In addition, Wal-Mart's high sales volumes means that it is generally regarded as a principal buyer so that it is able to obtain concessions from manufacturers including preferential wholesale prices (Dukes et al., 2006). An indirect effect of Walmart's purchasing power is that suppliers also appear to lower the prices they charge to other retailers in the same locale who stock similar

[3] One reason given by Borenstein and Rose (1994) to explain their positive findings was the widespread use of frequent flier points (FFPs) such that new entrants affect the less-frequent customers market but have little effect on frequent fliers due to high levels of brand loyalty.

goods (Chen, 2003). A second mechanism is through an increased competition effect in local markets. Hausman and Leibtag (2007) find a price effect from new competition when they examine customer benefits after the entry and expansion of Wal-Mart with the downward pricing pressure on incumbents being greater, the geographically closer they are to a new store. Wal-Mart's entry also had the effect of reducing wholesale prices. Gielens et al. (2008) argue that incumbents need to consider specialized and exclusive selling strategies or increase service augmentation to remain competitive given Wal-Mart's emphasis on low prices.

Studies of the gasoline retail market are more limited and have tended to focus on developed countries, such as the US and Canada. For example, Eckert and West (2004) investigate the difference in pricing behavior between Ottawa and Vancouver and argue that the substantial differences in pricing are likely to be caused by differences in market structure and market conduct. The authors point out that tacit collusion and coordination behavior contributed to short-run price stickiness and long-run price uniformity in Vancouver whereas in Ottawa the entry of maverick independent gasoline retailers eroded existing collusive behavior as new competitors sacrificed short run profits and undercut rivals to gain market share. A study of independent retailers in Southern California by Hastings (2004) following the acquisition of the Thrifty Oil Company in 1997, finds that retail prices rose once independent gasoline stations were converted into fully vertically integrated service stations. Their quasi-natural experiment predicts a 5 cent increase in the average retail price following the loss of one independent gasoline station. The ability of branded gasoline stations to exploit brand loyalty was also given as an explanation for an increase in prices as market share increases.

In a study of retail and wholesale gasoline prices in the US, Zimmerman (2012) finds that hypermarkets with a gasoline retail service exerted considerable downward pressure on nearby retail gasoline prices. Based on Hastings and Gilbert (2005) study of the US West Coast gasoline market, vertical integration is argued to be the primary reason for regional wholesale price differentials. In the market where integrated refiners have a large market share, they have a positive incentive to raise the unbranded wholesale price for its retailing rivals. Employing a pairwise approach, Holmes et al. (2013) find a cointegration of regional gasoline prices in the US. Their results suggest that the distance between states plays an important role in determining the speed of price converge. Yilmazkuday and Yilmazkuday (2016) list four sets of determinants of price dispersion in the retail gasoline sector: competitor density and station concentration levels; station characteristics (whether they have convenience stores or repair services); local demographic and economic conditions; and brand or contractual agreements.

A second strand of the literature examines the asymmetric movement of gasoline retailing prices. Maskin and Tirole (1988) first described the saw-toothed pricing pattern and developed the Edgeworth price cycle theory. Under a duopoly with alternating moves, competitors selling homogenous goods tend to undercut each other gradually until they approach the wholesale price. Following a war of attrition, one competitor relents and retail prices rebound rapidly before starting the next round of price cuts. Empirical evidence based on high frequency retail prices have been found in mature gasoline markets worldwide such as in Canada (Noel, 2007a,b, 2009; Eckert, 2002, 2003; Eckert and West, 2004; Byrne and de Roos, 2017), the US (Lewis, 2009; Lewis and Noel, 2011) and Australia (Bloch and Wills-Johnson, 2010; Byrne, 2012). Independent (non-branded) small firms have the greatest incentive to begin undercutting their larger rivals while large firms normally take the leadership in restoring prices (Eckert, 2003; Byrne et al., 2013). The Edgeworth cycle revolves faster, with a greater magnitude with less asymmetry in markets with more independent competitors (Noel, 2007a).[4]

[4] See Eckert (2013) for a detailed summary of empirical studies that examine different aspects of gasoline retailing.

Finally, only a few number of papers have examined the behaviour of energy prices in China. Ma et al. (2009) use 10-day energy spot price data for 35 major cities to investigate the extent of price convergence across China graphically and parametrically. The data reveal considerable price variation across the 31 mainland provinces for four major fuels (coal, electricity, gasoline and diesel) with price differences driven to a large extent by different energy reserve levels and transportation costs. As a consequence, cities close to gasoline production areas are predicted to enjoy a lower retail price. While gasoline and diesel prices behave fairly consistently, spatial price dispersion is still observed implying that the energy market for China remains segmented. Ma and Oxley (2012) confirm the result that energy prices in certain regional energy markets in China have converged but that this tends to be within groups of regions rather than across the whole country. Testing for club convergence and clustering, the evidence shows that several regional clusters for gasoline exist simultaneously but that they are becoming generally geographically connected as energy markets have become more open.

4.3 Data

4.3.1 Royal Dutch Shell in China

We begin with a brief review of the retail gasoline sector in China. Despite the complicated licensing process, multinational oil giants such as Shell, BP and Exxon have managed to access China's energy markets and have expanded their networks to include not just downstream retail gasoline service stations but also upstream refinery and fuel supply businesses. The reasons we focus on Shell are two-fold. First, Shell has the largest retail service network of the big four foreign companies (Shell has 862 stations in 48 cities compared to BP's 291 stations in 26 cities, Total's 202 stations in 41 cities, and Exxon's 14 stations across 10 cities). Second, Shell's official website provides detailed information on the location of each retail gasoline station (information not readily available for the other three companies). The presence of new international competitors has diversified not only the ownership of service stations but also the ownership of wholesalers.

From the late 1990s onwards Shell began to build jointly branded gasoline stations with local partners in a number of Chinese cities. The first Shell station was established in Tianjin in 1997, with 25% of the equity held by Tianjin Nongken State-owned Company. Shell then proceeded to develop a retail network that now covers the majority of metropolitan areas in the northern, southern, central and southeastern provinces. Shell's primary strategy was to find a local partner and then initiate a joint company within a given geographical area (which tended to be at the province level). By the end of 2014 Shell operated approximately 1,000 retail gasoline retail stations in China. The second stage of development was to build new service stations and to take over a number of existing unbranded service stations whilst continuing to seek new partnerships. At the current time all of China's major national oil companies have collaborative agreements with Shell, including China National Petroleum Corporation (CNPC), China Petroleum & Chemical Corporation (Sinopec), China National Offshore Oil Corporation (CNOOC) and Shaanxi Yanchang Group Company (YCG). These four oil companies are also the only companies that own petroleum exploration licenses for China.

The service station data that we use in this paper are available from the Shell website.[5] Figure 4.1 provides a geographical overview of Shell's gasoline service station footprint for 2013. The larger the symbol the higher the number of service stations in the city. The largest service station networks are in Shaanxi, Sichuan and Hebei provinces. For example, Yanchang and Shell Petroleum Company own more than 290 service stations in Shaanxi and Yanchang and Shell (Sichuan) Petroleum Company own 153 stations. In total Shell has a presence in 9 of

[5] See http://www.shell.com.cn/en/aboutshell/our-business-tpkg/china.html for details.

China's 31 provinces.[6] Table 4.1 complements Figure 4.1 by providing a summary of Shell's service station network also for 2013 including a number of other variables of interest. There is no obvious relationship between the location of Shell's gasoline stations and the production of gasoline per million people or per million vehicles. Figures 4.2 and 4.3 show the number of retail gasoline service stations per million people and per million vehicles for each of the 9 provinces with a Shell retail presence. Figure 4.4 shows the relationship between the gasoline production/surplus level and Shell's entry decision. A surplus in this context means that the province is a net exporter of gasoline products and a negative value implies that the province is a net importer of gasoline. The raw data suggests that Shell does not have an obvious tendency to locate its retail network in relatively high fuel production areas such as Shaanxi, Hebei and Shandong as the majority of provinces that Shell has chosen to locate are net fuel importing provinces such as Sichuan, Tianjin, Shanxi, Chongqing, Guangdong and Beijing. Table C.1 in the appendix lists each province ranked by gasoline production as well as consumption and surplus/deficit values.

[Figure 4.1, 4.2, 4.3 and 4.4 about here]

[Table 4.1 about here]

Within the 9 provinces listed in Table 4.1, Shell has a presence in 48 out of 94 prefecture-level or above cities.[7] However, due to a lack of gasoline price data we had to drop 37 cities from our sample. [8] We only include cities where the first entry year is between 2001 and 2012 which means excluding Tianjin (first entry year 1997) and Jinan (first entry year

[6]Shell has different partners in different regions for both upstream and downstream operations. According to the official website, there are five joint companies for the retailing business in China. They are Beijing Shell Oil Co. covering Beijing and Chengde city, Shell North China Petroleum Group Co. covering Tianjin, Hebei and Shandong, Yanchang and Shell (Guangdong) Petroleum Co. covering Guangdong, Yanchang and Shell (Sichuan) Petroleum Co. covering Sichuan, Yanchang and Shell Petroleum Co. covering Shaanxi and Shanxi.

[7]According to China.org.cn "*Prefectural-level cities are large and medium-size cities not including sub-provincial level cities. Normally, they are cities with a non-farming population of more than a quarter of a million.*" Source: http://www.china.org.cn/english/Political/28842.htm.

[8]Our gasoline price dataset includes prices for 62 cities.

2013). Our **Shell-presence group** is therefore 9 cities across 6 provinces with a first year of entry between 2001 and 2012. The nine cities are Beijing, Taiyuan, Guangzhou, Shenzhen, Chongqing, Chengdu, Zigong, Xian and Baoji. The dates for Shell's first year of entry and the number of stations are listed in Table 4.2. Our **non-Shell group** includes cities which have never previously had a Shell gasoline station. Tianjin (first entry year 1997) and Jinan (first entry year 2013) are excluded from both groups.

[Table 4.2 about here]

4.3.2 Retail and Wholesale Gasoline Prices in China

We now provide a brief overview of the gasoline pricing mechanism in China. To prepare for entry into the World Trade Organization (WTO), China adopted the world price of oil in June 1998. The pricing reform scheme issued by the State Development Planning Commission (SDPC) (renamed as National Development and Reform Commission in March 2003) proposed an adjustment to the monthly prices of crude oil and refined products based on Singapore market prices although the adjustment frequency did not become monthly until June 2000. China's previous pricing mechanism was a two-tier system which had remained unchanged since the early 1980s. In 2001 the Chinese government went further and linked domestic prices to international prices based on prices from the Singapore, Rotterdam, and New York markets with weights given by 6:3:1 respectively. At the same time crude oil prices were set by the two largest vertically-integrated oil companies instead of the SDPC. However, the government continued to provide guidelines and would make adjustments when the gap between domestic and international prices became too large. A new formula for setting baseline prices based on prices from the Brent, Dubai and Minas markets was introduced in January 2007. More recently there has been a narrowing of the interval and an increased frequency for price adjustments to be made. The latest refined products pricing scheme issued on March of 2013 allows the mutually supplied crude oil prices to be set jointly by Sinopec and PetroChina based on local refining conditions. Crude oil produced by CNOOC and other producers are set by the companies themselves. In the retail market, gasoline service station retailers can set their own prices as long as they are below a maximum price set by the NDRC for individual provinces and some major cities.

Generally speaking, each province has its own price cap. For example, the NDRC announced a decrease of 95 yuan/ton for wholesale and retail gasoline prices in July 7 2015. Shaanxi province then announced a decrease of 0.08 yuan/liter for gasoline, with a maximum price of 6.4 yuan/liter for the middle and north of the province and 6.48 for the south of the province. At the same time, Guangdong province set a maximum price of 6.13 yuan/liter for the province as a whole for the same product. A common perception of the energy market in China is that it is highly regulated and as such domestic fuel prices are underpriced relative to the world price which in turn encourages greater domestic consumption with implications for congestion and air pollution (Hang and Tu, 2007; Tan and Wolak, 2009). Drawing lessons from a widespread power shortage in 2008, Wang et al. (2009) argue that the centrally planned policy-oriented pricing mechanism encouraged excessive growth in heavy industry, and hence was inconsistent with a strategy to promote energy-conservation and sustainable development.

This paper analyzes the pricing behavior of three different grades of fuel. The current industrial classification for automotive gasoline products in China is GB 17930 "Automotive Gasoline". Within this classification there are three type of gasoline that we label Gas#90, Gas#93 and Gas#97. The number associated with each product represents the octane rate. For example, Gas#97 gasoline contains 97% iso-octane and 3% n-heptane. The gasoline octane number is designed to be compatible with the compression ratio of the engine. If an engine with a high compression ratio is used with a low octane gasoline the engine tends to knock, which can cause problems such as piston splintering and piston ring breakage. If an engine with a low compression ratio is used with a high octane gasoline, the ignition timing may be altered, which can cause incremental sedimentation inside the engine cylinder thus shortening engine life (Sinopec Corp. 2014). The compression ratio is an important structural parameter for the engine. Generally speaking, a high compression ratio indicates high thermal efficiency giving the automobile more power, grater acceleration and a higher maximum speed. Hence, high performance cars need higher quality gasoline (a higher octane percentage).

The initial gasoline price data is a panel dataset collected by the China Price Monitoring Centre (CPMC) on every 5th, 15th and 25th day of each month. From 2001 to 2012, spot prices were obtained from several (normally 2-5) permanent anonymous services stations for a number of different gasoline varieties. Since there is no brand information for the stations from which the price information is taken, we simply take the arithmetic mean between monitoring stations as the market average price for that city. For our analysis, we aggregate spot price data at the annual average level for the following reasons. First, the gasoline pricing regime and the price cap mechanism during the study period have slowed down the speed of price adjustment significantly. Figure C.1 in the Appendix presents the spot price trend from the anonymous station no.1 in each of our sampled cities. For most cities the price changes 2 to 5 times a year although the price is collected every 10 days.[9] Using high frequent data will cause a large amount of repeated records in our sample and this may lead to an estimation bias of Shell's entry effect. Second, due to a lack of the precise date of Shell's entry into a city, using annual price data enable us to match the entry as well as other economic and demographic variables on a yearly basis. Finally, many retail sectors show a strong seasonality and using annual data avoids the undesired seasonal fluctuation.

[9] A similar example can be found in Figure 6 and 7 in Ma et al. (2009)

4.4 Identification Strategy

Our methodological approach is to use a difference-in-differences (DID) pairwise estimator to help us identity the causal relationship between price dispersion across cities and the entry of Shell into a local market. We first match each of the Shell-presence cities with several non-Shell cities using propensity score matching (PSM) technique. The matching procedure includes a number of macroeconomic control variables to address self-selection concerns related to the difference in development levels between cities.[10] Second, following Pesaran et al. (2009) and Holmes et al. (2013), we take the absolute gasoline price differentials between any two cities in a group including one Shell-presence city and its corresponding matched non-Shell cities. Since there was considerable deregulation in China's energy market during our period of study, taking differences removes the effect of common shocks that impacted all cities in a given year. By taking differences relative to another city or cities instead of simply taking the group mean also allows us to examine the impact of distance on price dispersion. Finally, we adopt the DID method on the bivariate price differentials. The coefficient on the DID interaction term measures the entry effect of Shell on the price dispersion in a given year in China. In a sense, a DID model on differential data is a triple difference model.

We employ the PSM approach matching on a range of city-level characteristics which are GDP per capita, population density, average wages, passenger traffic by highway and the price for Gas#90).[11] The results of our initial matching are presented in Table 4.3. In Table

[10]The usual DID approach selects the treatment and control groups based on a different application of a policy across, for example, geographical regions where a region is allocated to either a treatment group (policy applied) or a control group (no policy applied). However, if the regions selected to receive intervention were picked because of certain regional characteristics, the treated and control groups may have different pre-policy trends. Since conducting a natural experiment in economic research is rare, finding an efficient counterfactual for the treated units of analysis becomes a precondition for the construction of the DID framework. PSM allows the researcher to generate matched controls for each treated unit of analysis with post-matching balancing tests used to ensure that for a given PSM, the DID approach is appropriate.

[11]See Table C.2 in the appendix for definitions of our matching variables. All monetary values are deflated in 2005 prices using a province level Customer Price Index (CPI). Estimation of propensity scores using a logit

4.4 we present the results from post-match balancing tests which assess the accuracy of our PSM matching method for individual variables as well as the overall covariate balance. The results show that the balancing assumption is satisfied both individually and overall.

[Table 4.3 about here]

[Table 4.4 about here]

After matching we adopt the pairwise approach and calculate the extent of any absolute price differences between a Shell-presence city and its corresponding matched controls. The pairwise approach is recently developed by Pesaran (2007b) who tests the output and growth convergence and Pesaran et al. (2009) who test the Law of One Price in 50 countries over the period 1957 to 2001. Holmes et al. (2013) employ the pairwise approach to examine the gasoline market integration in the US and find a strong evidence of gasoline price convergence.[12] For cities i and j in group g, the price differential of each of our gasoline fuel types z in time t is defined as:

$$Dispersion_{z,ij,t} = |log(Price_{z,i,t}) - log(Price_{z,j,t})|$$

For convenience we use pair p to denote a combination of city i and j.

$$Dispersion_{z,p,t} = |log(Price_{z,i,t}) - log(Price_{z,j,t})| \qquad p = 1,2\ldots\sum_{g=1}^{9} C^2_{G_g}$$

estimation are presented in Table C.3. Overall coefficients were significant and the pseudo-R square reveals that the equation explains 21.9% of the variation and indicate the potential benefit of matching the sample according to propensity scores (Baser, 2006). The Gas#90 price is included in the matching as a benchmark of local gasoline price level and is insignificant in both the logit regression and post matching tests. Our results suggest that the local gasoline price is not an important consideration for Shell to make the entry decision.

[12] To be precise, the pairwise approach used in this paper is part of the the pairwise method mentioned in Pesaran (2007b), Pesaran et al. (2009) and Holmes et al. (2013). In these three papers a variety of unit root tests are conducted on all possible $N(N-1)/2$ bivariate differentials between any pairs of N countries or states.

group g contains 1 treated city and $(G_g - 1)$ control cities which implies $\sum_{g-1}^{9} C^2_{(G_g-1)}$ treated pairs and $\sum_{g=1}^{9} C^2_{(G_g-1)}$ control pairs in total.

Before modelling the causal relationship between price dispersion and foreign entry, we characterize some general patterns of price dispersion that we find in the data. Following Fan and Wei (2006) and Holmes et al. (2013) we examine fluctuations in retail gasoline prices taking into account the distance between cities and a time trend given by:

$$Dispersion_{z,p,t} = \gamma_0 + \gamma_1 Trend_t + \gamma_2 Distance_p + \gamma_3 Distance_p^2 + \varepsilon_t$$

Table 4.5 presents the results for a simple OLS regression examining the impacts of a linear trend and distance on price dispersion. The spatial distance between pairwise cities is calculated using the great circle formula according to information on the latitude and longitude of the centroid of the cities. The immediate observation is the importance of distance. The further two cities are away from each other, the greater the absolute price difference. In columns (4) (5) and (6) where we also include squared distance terms, we find a positive impact of distance on price dispersion for all of our three products but at a decreasing rate. Our finding is in line with Holmes et al. (2013) who find an asymmetric relationship between the distance and the speed at which gasoline prices converge to the long-run equilibrium. The negative and significant time trend for our period of analysis also suggests a general reduction in price dispersion for Gas#93 and Gas#97 but a significant and positive effect on price dispersion for Gas#90. In the following analysis distance is considered as a pair-specific effect and year-specific effect accounts for the linear trend. Other controls are also included.

[Table 4.5 about here]

Since one of our key testable hypotheses is whether price dispersion changed after Shell's entry, for each of our pair cities, the treatment effect after s years of entry is measured as:

$$Dispersion^1_{z,p,t+s} - Dispersion^0_{z,p,t+s}$$

where the superscript implies whether a pair of cities is being treated $(Treatment = 0,1)$ and the subscript $t+s$ implies $s\,(s = 0,1,2)$ years after the entry date t. However, the second term in the equation is unobservable. Based on the results of our matching procedure, each treated city has several matched controls which have similar economic and demographic characteristics. Therefore, the price dispersion between two valid control cities within one group are regarded as the appropriate substitution for the unobservable term. As a result, the average treatment effect on the treated (ATT) given by:

$$\begin{gathered}
ATT = E[Dispersion^1_{z,p,t+s} - Dispersion^0_{z,p,t+s}|Treatment_{p,t} = 1] \\
= E[Dispersion^1_{z,p,t+s}|Treatment_{p,t} = 1] - E[Dispersion^0_{z,p,t+s}|Treatment_{p,t} = 1] \\
= E[Dispersion^1_{z,p,t+s}|Treatment_{p,t} = 1] - E[Dispersion^0_{z,p,t+s}|Treatment_{p,t} = 0] \\
s = 0,1,2 \qquad p = 1,2\ldots\sum_{g=1}^{9} C^2_{G_g}
\end{gathered}$$

Hence, our pairwise DID estimator, based on the matched sample, is given by:

$$ATT = \frac{1}{\sum_{g=1}^{9}(G_g - 1)} \sum [\Delta_s Dispersion^1_{z,p} - \Delta_s Dispersion^0_{z,q}]$$

where $\Delta_s Dispersion^1_{z,p}$ is the difference in absolute price differential after s years of the entry for the treated pair p, and $\Delta_s Dispersion^0_{z,q}$ is the difference in absolute price differential after s years of entry for control pair q.

Disentangling the different sources of price dispersion is important if we are to identify the causal relationship between Shell's entry and the subsequent behavior in gasoline prices. Based on Vita (2000) and Zimmerman (2012), a vector of covariates are taken into account in the measurement of price dispersion including income per capital, population density, average wage per worker, population at the end of the year and highway passenger traffic. According to Borenstein and Rose (1994), price dispersion may arise from two sources, namely cost variations and discriminatory pricing. However, it is difficult to separate the cost-based dispersion from the discrimination-based dispersion because of market heterogeneity. For example, on one hand, management costs and transaction costs per sale could be lower in high population density cities than in relatively small cities due to economies of scale. It implies that retailers can set lower prices in these locations to acquire greater market share, even by compensating for losses in small cities. On the other hand, the demand elasticity for fuel may be lower in larger cities which provides an incentive to price discriminate. Hence, we control for the relationship between price dispersion and factors that might indicate a basis either for cost variations or discrimination within a DID framework. Considering the possibility of a delayed impact of Shell's entry and the fact that the first Shell station might only have a minor effect on the local market, we include lags and the corresponding interaction terms for Shell's entry decision. We therefore estimate a basic and an extended model given by.

Basic framework

$$\begin{aligned} Dispersion_{z,p,t} &= \alpha + \beta_1 Treatment_p + \beta_2 Post_{p0} + \beta_3 Treatment_p \times Post_{p0} \\ &+ \boldsymbol{\Delta_p Control \cdot \gamma} + \sum_p \gamma_p Pair_p + \sum_t \delta_t Year_t + \varepsilon_{z,p,t} \end{aligned}$$

Extended framework

$$Dispersion_{z,p,t} = \alpha + \beta_1 Treatment_p + \beta_2 Post_{p0} + \beta_3 Treatment_p \times Post_{p0}$$
$$+\beta_4 Post_{p1} + \beta_5 Treatment_p \times Post_{p1} + \beta_6 Post_{p2} + \beta_7 Treatment_p \times Post_{p2}$$
$$+\boldsymbol{\Delta_p Control} \cdot \boldsymbol{\gamma} + \sum_p \gamma_p Pair_p + \sum_t \delta_t Year_t + \varepsilon_{z,p,t}$$

Subscript z represents our three gasoline products Gas#90, Gas#93 and Gas#97 described in previous section. Subscript p indicates each combination of two cities. $Treatment_p$ is a binary variable indicating whether one city in the pair has been or will be entered by Shell. $Post_{p0}$, $Post_{p1}$ and $Post_{p2}$ are dummy variables representing the entry year, one year and two years after entry respectively. $\boldsymbol{\Delta_p Control}$ represents the covariate matrix including the differences in income per capital, population density, average wage of workers, population at the end of year and passenger numbers travelling by highway. Our measure of the absolute differences in the independent variables is calculated using the same order between cities as we used to generate our price dispersion variable, which were randomly assigned. $Pair_p$ and $Year_t$ represent pair-specific fixed effects and time fixed effects respectively and $\varepsilon_{z,p,t}$ is the error term. Table 4.6 presents a summary of our differenced variables and shows, for example, that the average price dispersion for Gas#90 retail price between any two matched cities in our sample is approximately 4% and slightly lower than those for Gas#93 and Gas#97.

[Table 4.6 about here]

4.5 Results

Table 4.7 presents our difference-in-difference estimation results for the determinants of retail price dispersion for the whole sample. Columns (1), (4) and (7) present the results from a fixed effects regression for each of our three gasoline products. Columns (2), (5) and (8) control for a number of additional social economic factors while columns (3), (6) and (9) include lags and interactions with the treatment indicator to allow us to consider the longer term impact. Year specific and individual pair effects are included in all regressions. Coefficients are estimated with robust standard errors.

[Table 4.7 about here]

According to the Difference-in-Difference model the $Treatment$ variable takes a unit value of one if a city in the pair has a Shell retail station or will have a Shell retail station. $Post_0$ is equal to one since the entry year is set to the same value for treated and control cities within one group. Our results presented in Table 4.7 reveal a positive and then negative impact of Shell's entry on the degree of price dispersion for highly refined products as indicated by the $Treatment \times Post_0$ and $Treatment \times Post_1$ variables. The degree of price dispersion between Shell populated cities and non-Shell populated cities increases by approximately 1.3 to 1.5 percentage points before falling by 1.5 to 1.8 percentage points in the following period.

When we compare across gasoline types it appears that Shell's entry into a city tends to have a larger impact on the price dispersion of highly refined gasoline rather than the more regular gasoline products. The coefficients on the interaction term for Gas#93 and Gas#97 are similar in both the range and the statistical significance, while the elasticity for Gas#90 tends to be lower and insignificant except for the third period after entry. There are two possible explanations. First, highly refined gasoline tends to be more profitable (had previously higher margins). The market for high performance fuels is also likely to be more attractive to foreign firms where they may also have a technological advantage coupled with higher advertising and marketing budgets. For the 862 Shell service stations over the whole of China, more than 95 percent of the stations sell highly refined gasoline. In contrast, only a small number of service stations in Beijing, Shandong and Guangdong sell the regular gasoline product. Furthermore, unbalanced entry implies that the two large government-owned vertically-integrated oil companies, Sinopec and PetroChina, have greater monopoly power in the production and retail of regular gasoline. With a large market share occupied by incumbents, the average price level is less likely to respond to or be influenced by the entry of international retailers such as Shell and such an effect is confirmed by our results.

Second, the cross-elasticities of demand from consumers tend be different between Gas#90, Gas#93 and Gas#97. According to a survey by Sohu, Gas#90 is used mainly by commercial vehicles such as taxis and buses. These operators prefer low grade gasoline in order to reduce operating costs, while private car owners tend to pay more attention to the condition of their vehicle and are more likely to use higher grade gasoline. Given private car owners are also more likely to have a preference for quality and non-fuel services, the entry of Shell is more likely to increase competition in the Gas#93 and Gas#97 markets and should therefore have a larger impact on local market prices. In addition, commercial vehicles are often tied into long-term contracts with incumbents and are thus less likely to change brand in response to price competition. As a result, the market price distribution for Gas#90 is less likely to be influenced by the entry of a foreign competitor.

Turning to the other covariates, we find a negative effect from the absolute difference in GDP per capita between cities for Gas#93 and Gas#97 but a positive effect on the absolute dispersion of Gas#90. Of the remaining explanatory variables, average wage per employee tends to be a cost shifter while population and highway passenger traffic numbers are demand shifters. According to Lin (1985) population density plays a mixed role and could be regarded as both a cost and a demand shifter. In our case, when we consider the whole sample, greater differences in these variables tends to exert a negative impact on price dispersion. The dispersion of average wage has a negative and statistically significant impact on all of our three products. Differences in the population and passenger traffic by highway are also significant and negative determinants of price dispersion for Gas#90.

In the next stage we investigate whether our results are driven by a segmented market effect. To do this we run regressions for different regional markets by identifying whether the treated city is located in the western region for each gasoline type and using the full specification including lags on the entry decision.[13] The results are presented in Table 4.8. The first three columns of Table 4.8 are based on east/central subsample while columns (4) to (6) are for the subset of western regions. At the first glance it appears that Shell's entry had a greater and more immediate impact on price changes in western regions. The positive impact following by the reduction in prices occurs from the first period of Shell's entry for western cities while it starts from the second period after entry in east/central area. One explanation could be the regional convergence clusters theory Ma and Oxley (2012) which argues that the eastern energy market is more mature and hence has a higher level of competition so firms are more likely to be price takers.

[Table 4.8 about here]

4.6 Pricing Mechanisms

As one of a leading group of energy and petrochemical companies, Shell has various businesses in China including upstream and downstream activities. Its size and expertise means that it can undertake complex projects using world leading innovative technologies. As a new entrant, Shell has the managerial skills, scale and financial backing to be considered an efficient competitor. Following Basker (2005) study on Wal-Mart's entry effect on local

[13]The treated cities located in the western region are Chongqing, Chengdu, Zigong, Xian and Baoji. Beijing, Guangzhou and Shenzhen are regarded as eastern cities and Taiyuan is considered as a central city.

prices in the US and Hastings (2004) about vertical relationships and competition in the retail gasoline market we now investigate two potential mechanisms that may affect price dispersion.

4.6.1 The market-specific mechanism

The market-specific mechanism works through retail competition at the local market level. New foreign gasoline retailers are assumed to exert competitive pressure in localized gasoline markets. Previous empirical studies suggest an inverted relationship between the degree of market diversification and gasoline prices (Hastings, 2004; Zimmerman, 2012). To account for Shell's uneven network distribution across China, we construct a measure of the degree of competition from Shell based on the number of Shell stations in an individual market scaled by the maximum number of Shell stations in a city (in our dataset this is Xian with 113 stations).[14] We calculate our competition indicator in the entry year as:

$$Competition_{it}^{0} = \frac{Total\ number\ of\ Shell\ stations\ in\ city\ i}{Max\ number\ of\ Shell\ stations\ in\ a\ city} \times Post_{i0}$$

The delayed effect of increased competition is captured by the corresponding indicators generated with $Post_{i1}$ and $Post_{i2}$ giving us our $Competition^1$ and $Competition^2$ variables. Table 4.9 presents our estimation results for the impact of the extent of Shell's competitive impact on the retail price for our three different types of gasoline. Note that the unit of analysis is an individual city rather than a comparison across cities which implies that the left hand side variable is simply the price level rather than a measure of price dispersion. The first three columns use the overall matched sample and the final three columns consider

[14] Since retail networks are generally built gradually over time, ideally our Shell competitive index should also increase over time. However, we only have the total number of stations located in a city and not the opening date for each individual station. Using the total number of stations enables us to get a rough approximation of the degree of Shell's presence in a local market.

the western area only (sample size issue means that we are unable to report the eastern and central city results). A negative and statistically significant coefficient on the impact of competition on price for Gas#93 and Gas#97 shows that Shell's presence in a local market increases competition and leads to a reduction in the retail price for two of our three gasoline products immediately after Shell's entry.

Our results suggest that in the year of entry in Xian, for Gas#93 and Gas#97 prices fall by between 4.2 and 5.0 percent (column 2 and 3 in Table 4.9). Hence, the impact of Shell's entry on the price level in a treated city tends to decrease relative to the price in the control group of cities.[15] The results suggest that the initial positive effect of entry on price dispersion is driven by price falls in treated cities and that this effect is particularly true for highly refined products. Similarly, the rebound in prices in the second stage indicated by the coefficient of $Competition^1$ captures the decrease in price dispersion in Table 4.7. One explanation for these overall price dynamics comes from the Edgeworth price cycle hypothesis that was discussed in the literature review where an asymmetric pattern of price changes is comprised of numerous small prices decreases that are then interrupted by occasionally large price increases (Maskin and Tirole, 1988; Noel, 2011). The argument follows that after the entry of new competitor, firms tend to undercut each other (normally initiated by smaller firms) in order to achieve a greater market share. Eventually, a restoration of the higher price occurs, generally by parties with large market shares, and a new sequence of undercutting is initiated (Noel, 2007a; Eckert, 2003).

As we found previously, the impact of competition is driven mainly by a strong entry effect in western regions of China and is again more significant for highly refined gasoline. Turning

[15] If we take Xian as an example a 4.2 and 5.0 percent decrease (Column (2) (3) in Table 4.9) means a price reduction of approximately 230 and 290 yuan/ton (0.17 and 0.21 yuan/liter) for Gas#93 and Gas#97 after Shell's entry compared with non-Shell cities everything else equal. Although economically this is small effect these numbers feel intuitively plausible given the characteristics of the retail gasoline market in China.

to our other controls, we find a generally positive impact on gasoline prices from population density which could be considered as a demand driver.

[Table 4.9 about here]

4.6.2 The aggregation mechanism

The second mechanism we investigate is the impact of entry on the wholesale price of gasoline and how this is affected by Shell's relationship with local partners who can share valuable resources and information which could take a long time to develop such as government relationships, supply networks and knowledge of local markets (Lu, 2010). Over the last ten years, Shell has developed a number of partnerships with domestic companies and has built relationships with all of the major national oil companies in China, including China National Petroleum Corporation (CNPC), China Petroleum & Chemical Corporation (Sinopec), China National Offshore Oil Corporation (CNPPC) and Shaanxi Yanchang Group Company (YCG). By doing so Shell has achieved end-to-end integration of the entire value chain from upstream refineries to downstream retail gasoline stations. The effect on prices could be two-fold. First, companies such as Shell can bring the global management practices to bear and second, they have experience operating complex global supply chains. This effect is likely to be stronger when foreign firms partner with existing refineries run by the large incumbents in the Chinese market.

In Table 4.10 we present the results for the entry effect on the dispersion of the purchase price faced by gasoline service stations across China and can be compared to the results in Tables 4.7 and 4.8. If Shell's entry leads to changes in the average wholesale price across different cities then local retailers may also be affected and even benefit from Shell's negotiations with upstream industries in order to set similar retail prices in different local markets. For

Gas#97 the coefficients on the first interaction term $Treatment \times Post_0$ are always positive and significant which suggests that the entry of Shell did lead to a significant impact on wholesale gasoline prices. In Table 4.11 we also break down the effect by region and again find that the entrant effect on market wholesale price dispersion is higher for western markets for Gas#97. In Table 4.12 we estimate the competitive effect with the level value of wholesale prices. Similarly, we also find that the increase in price dispersion is driven by a reduction in prices in treated cities. Hence, it appears that customers benefit more from a more general impact of Shell on wholesale prices.

[Tables 4.10, 4.11 and 4.12 about here]

4.7 Robustness Checks

In this section we conduct a series of robustness checks. The first is to implement a placebo-control test based on the potential control cities. Within the group of non-Shell cities, a random sample of cities with random entry years were selected as the treatment group (we chose 6 to 10 cities as the treated cities with entry years between 2002 and 2011) and implemented our pairwise DID estimator to investigate the first, second and third period entry effect. The process was simulated 300 times and no significant entry effects were found for any period after the assumed year of entry. This gives us confidence that we are capturing the impact of Shell's entry on prices.

Second, although Shell has the largest gasoline retail network, it is not the only foreign oil company to have entered China's gasoline retail market. British Petroleum (BP), Total S.A. and Exxon have also made inroads into China's retail market since the beginning of the 1990s. One concern is that our potential control cities also include international retailers which may lead to an underestimate of the entry effect of Shell. Therefore, we use data from the top four international retailers' entry in China combined with our gasoline price dataset. A city is labeled as a treatment city if any one of the four retailers has opened a gasoline retail station in that city. The treatment date was set as the year of the first retailer's entry.[16] Although we replicated Tables 4.7 – 4.11 we present only the main results. The other tables are available from the authors upon request.

[Table 4.13 about here]

Table 4.13 presents the entry effect results for four retailers on the retail prices dispersion for Gas#90, Gas#93 and Gas#97. Including lagged entry period and various covariates in column (3), (6) and (9), the entry of an international retailer into a local market leads to a decrease in the absolute price dispersion for Gas#90 and increases and then a fall for Gas#93 and Gas#97. Again, the entry effect tends to be stronger for highly refined products (Gas#93 and Gas#97) rather than that the regular product (Gas#90). The coefficients are similar with those in Table 4.7.

4.8 Conclusions

The recent fall in crude oil prices provides China with an opportunity to implement further energy market reforms. Promoting a more market-orientated pricing regime through a diversified ownership structure is an integral part of such a process. After the opening up of the retail and wholesale market many of the world's largest multinational oil companies sought access to China's energy industry and in many cases they expanded rapidly. In this paper we examine Shell's entry into China and investigate the entry effect on gasoline price

[16]The location and entry date information are collected manually on Baidu Map and local newspaper/news website, which makes the results are only indicative.

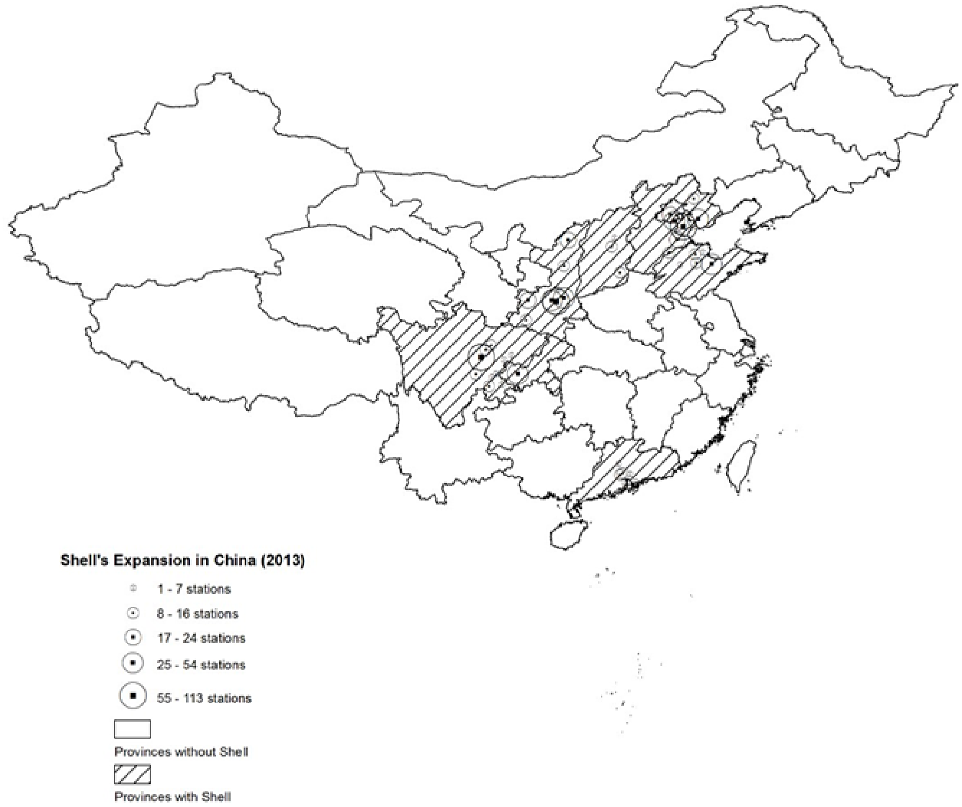
convergence across China for three different type of gasoline on both the retail and wholesale prices.

Combining a pairwise approach and the difference-in-difference model we show that the absolute price differential between cities where Shell has a presence and a similar city without Shell increased by between approximately 1.3 and 1.5 percent compared to the price differential between any two non- Shell targeted cities. The increased price gap was found to close again in the following two years. Highly refined gasoline products tend to be the most affected. The price effect is largest for Western China where the competitive effect of a large new entrant is felt most keenly. Two potential mechanisms, the market-specific mechanism and the aggregation mechanism, explain the increase in the price gap. The market-specific mechanism works through the local market and retail prices for premium products (Gas#93 and Gas#97) where we find a price fall between 4.2 to 5.0 percent in the entry year before prices rise again by between 2.4 to 3.2 percent over the next two years. When we consider the aggregation mechanism we find that the dispersion of the wholesale price for Gas#97 follows a similar pattern. The difference in the magnitude of the impact across our three gasoline products and two regions holds. The main results are robust to a placebo-control test and controlling for the entry of other foreign multinational retailers.

Deregulation and market liberalization of China's energy market has been in progress for more than ten years. The outcome appears to be positive for consumers who have experienced lower prices for gasoline. With China's development entering a period of lower growth, energy consumption has slowed dramatically. During the first ten years of 21st century, the annual average growth rate for energy consumption was 9.4%. Between 2011 and 2014 this has fallen to 4.3% and is expected to grow around 3% for the next five years. Hence, China is likely to have sufficient energy supplies to meet this lower than expected demand. Hence, politically, the current period could represent an ideal time to pursue further reform of the energy market. One example of the progress being made is the, so-called, “mixed-ownership” reforms when in 2014 Sinopec sold off around 30% of its retailing business to private investors raising more than 100 billion yuan. Efforts to encourage mixed ownership in upstream exploration by, for example, allowing oil companies to enter the oilfield services sector should also be considered. Reform of the resource tax system is also an area that needs careful attention (Huang, 2015).

Figures and tables

Fig. 4.1 The location of Shell service stations in China (2013)



Source: Shell website http://www.shell.com.cn/en/aboutshell/our-business-tpkg/china.html

Fig. 4.2 Number of Shell service stations per million people (2013)

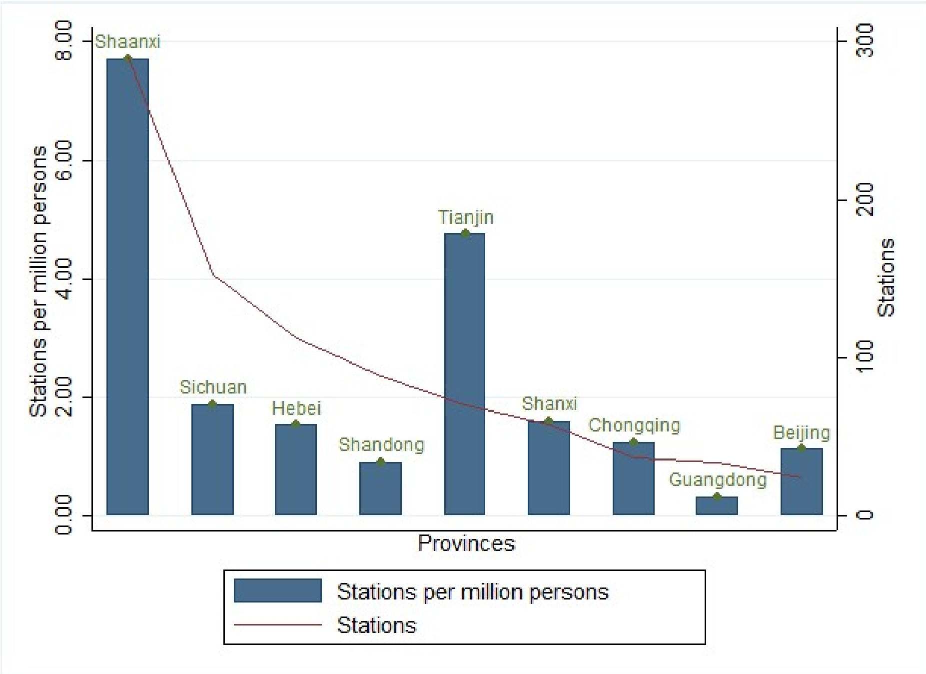


Fig. 4.3 Number of Shell service stations per million vehicles (2013)

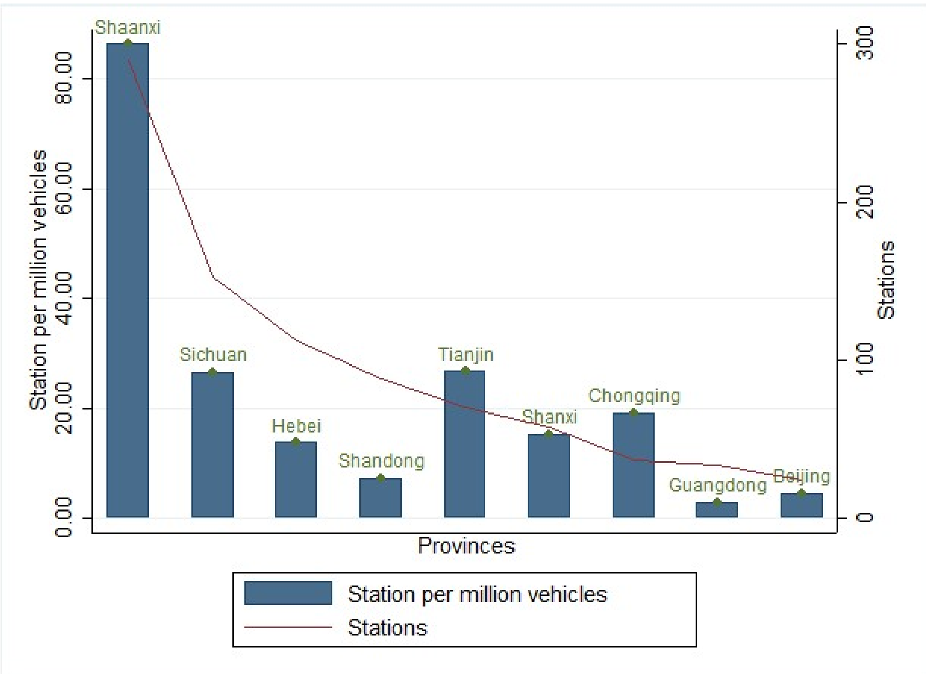
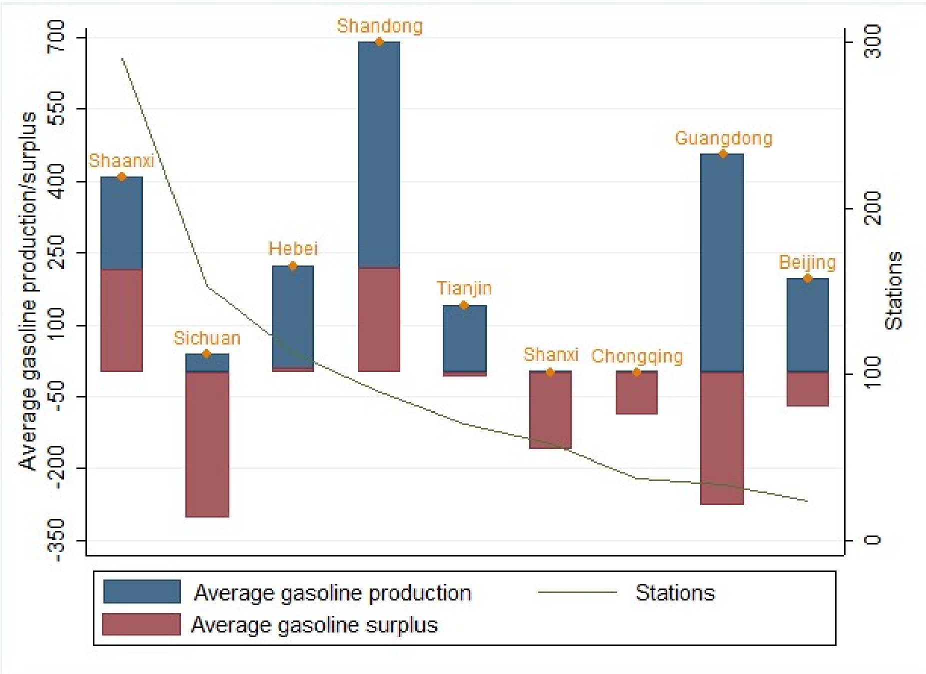


Fig. 4.4 Average gasoline production and surplus at the provincial level (2001-2012)



Source: China Energy Statistical Yearbooks. Unit in 10,000 tons.

Table 4.1 A summary of Shell service station network across 9 provinces (2013)

Province	Stations	Population	Vehicles	Stations per million persons	Stations per million vehicles	Average annual gasoline production (10,000 tons)	Average annual gasoline consumption (10,000 tons)	Average gasoline surplus/deficit (10,000 tons)
Shaanxi	290	3764.00	336.08	7.70	86.29	426.10	197.89	228.21
Sichuan	153	8107.00	573.03	1.89	26.70	39.59	355.17	-315.58
Hebei	113	7332.61	816.29	1.54	13.84	227.12	219.74	7.38
Shandong	89	9733.39	1199.71	0.91	7.42	722.32	492.47	229.85
Tianjin	70	1472.21	261.58	4.75	26.76	141.88	153.17	-11.28
Shanxi	58	3629.80	378.27	1.60	15.33	2.01	168.87	-166.86
Chongqing	37	2970.00	192.77	1.25	19.19	0.42	91.78	-91.36
Guangdong	34	10644.00	1177.37	0.32	2.89	465.21	767.04	-301.83
Beijing	24	2114.80	517.11	1.13	4.64	200.49	281.18	-80.69

Note: Data sources from China Data Online and China Energy Statistical Yearbook. Units for population and vehicles are 10,000 persons and 10,000 units respectively. Average annual gasoline production, consumption and deficits are calculated for the period 2001 to 2012.

Table 4.2 Number of Shell service stations in our nine treated cities (2001-2012)

City	Province	Stations	First entry date
Beijing	Beijing	24	2003
Taiyuan	Shanxi	13	2010
Guangzhou	Guangdong	9	2007
Shenzhen	Guangdong	1	2007
Chongqing	Chongqing	37	2007
Chengdu	Sichuan	68	2005
Zigong	Sichuan	4	2005
Xian	Shaanxi	113	2009
Baoji	Shaanxi	20	2010

Note: Data sources from Shell China http://www.shell.com.cn/en/aboutshell/our-business-tpkg/china.html. First entry date are collected from the internet.

Table 4.3 Treated and control groups (2001-2012)

Group	Treated cities	Control cities	Group	Treated cities	Control cities
1	Beijing	Datong	6	Chengdu	Fuzhou
1	Beijing	Hefei	6	Chengdu	Haikou
1	Beijing	Nanchang	6	Chengdu	Hefei
1	Beijing	Pingliang	6	Chengdu	Nanchang
1	Beijing	Wuhan	6	Chengdu	Wuhan
1	Beijing	Xiamen	6	Chengdu	Zhengzhou
2	Taiyuan	Datong	7	Zigong	Dalian
2	Taiyuan	Jiaxing	7	Zigong	Haikou
2	Taiyuan	Pingliang	7	Zigong	Nanning
2	Taiyuan	Wuhan	7	Zigong	Qingdao
2	Taiyuan	Xingtai	7	Zigong	Quanzhou
2	Taiyuan	Xuzhou	7	Zigong	Shenyang
3	Guangzhou	Nanjing	7	Zigong	Zhengzhou
3	Guangzhou	Xiamen	8	Xian	Nanjing
3	Guangzhou	Xingtai	8	Xian	Wuhan
4	Shenzhen	Jiaxing	8	Xian	Xiamen
4	Shenzhen	Xingtai	8	Xian	Xingtai
4	Shenzhen	Xuzhou	8	Xian	Xuzhou
4	Shenzhen	Zhoukou	9	Baoji	Dalian
5	Chongqing	Nanjing	9	Baoji	Fushun
5	Chongqing	Shanghai	9	Baoji	Guiyang
			9	Baoji	Shijiazhuang
			9	Baoji	Yantai

Note: Only cities which have never been entered by Shell are included as possible control cities. The PSM procedure is based on nearest neighbor matching. A robustness check using radius matching gives similar results which are available upon request.

Table 4.4 Post-matching tests for balanced assumption

Variable	Matching	Mean		%Bias	%Bias	T test	P-value	V(T)
		Treated	Control		Reduction			/V(C)
GDP per capital	Unmatched	10.35	10.15	40.00		2.21	0.03	0.81
	Matched	10.35	10.29	11.60	70.90	0.46	0.65	0.64
Population density	Unmatched	6.46	5.98	90.30		4.72	0.00	0.59
	Matched	6.46	6.42	7.60	91.60	0.35	0.73	0.76
Average wage	Unmatched	10.23	10.05	58.60		3.22	0.00	0.79
	Matched	10.23	10.21	3.80	93.50	0.18	0.86	1.24
Passenger traffic by highway	Unmatched	9.16	9.00	17.30		1.16	0.25	1.91
	Matched	9.16	9.20	-4.40	74.40	-0.20	0.85	2.41
Gas#90	Unmatched	8.66	8.65	3.60		0.18	0.86	0.51
	Matched	8.66	8.68	-8.50	-139.00	-0.45	0.66	1.07

Sample	Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.21	54.06	0.00	41.90	40.00	132.90	0.64	0.00
Matched	0.01	0.52	0.99	7.20	7.60	16.80	1.40	20.00

Notes: The first table compares the extent of balancing for each variable. The standardized percentage bias (column 5) is the sample mean difference between the treated and non-treated sub-samples as a percentage of the square root of the average of the sample variances in both sub-samples (Rosenbaum and Rubin 1985). A lower bias percentage implies a better match with the covariates. Column 7 shows the t-test for equality of means in both samples. The high p-values in the final column indicate that there is no significant difference between the treatment and the control group. The variance ratio of treated over non-treated is displayed in the last column and it should equal to 1 if there is perfect balance. The second table calculates the overall measures of covariate balance. The likelihood-ratio test of the joint insignificance and the corresponding p-values are present in column 2 and 3. The mean and median bias as summary indicators of the distribution of the absolute bias are shown in column 4 and 5. Robin's B (the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group) is recommended to be less than 25 and Rubin's R (the ratio of treated to (matched) non-treated variances of the propensity score index) is recommended to be between 0.5 and 2 for the samples to be considered sufficiently balanced (Rubin, 2001).

Table 4.5 The impact of distance on price dispersions (OLS regression 2001-2012)

Variables	(1) Gas #90	(2) Gas #93	(3) Gas #97	(4) Gas #90	(5) Gas #93	(6) Gas #97
Trend	0.0027***	-0.0013***	-0.0015***	0.0026***	-0.0013***	-0.0016***
	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
Log(Distance)	0.0105***	0.0071***	0.0048***	0.0690***	0.0371**	0.0592***
	(0.0015)	(0.0012)	(0.0011)	(0.0191)	(0.0148)	(0.0140)
Log(Distance)^2				-0.0041***	-0.0021**	-0.0038***
				(0.0014)	(0.0011)	(0.0010)
Constant	-5.3664***	2.5557***	3.0918***	-5.3674***	2.5497***	3.0776***
	(0.7703)	(0.6271)	(0.6388)	(0.7606)	(0.6230)	(0.6300)
Observations	1,262	1,316	1,302	1,262	1,316	1,302
R-squared	0.0572	0.0396	0.0321	0.0640	0.0428	0.0430

Note: Robust standard errors in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Table 4.6 Description of the variable dispersion (2001-2012)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Δlog (Gas#90 retail price)	1,262	0.0402	0.0491	0.0000	0.2716
Δlog (Gas#93 retail price)	1,316	0.0354	0.0373	0.0000	0.2197
Δlog (Gas#97 retail price)	1,302	0.0356	0.0361	0.0000	0.2030
Δlog (Gas#90 wholesale price)	1,116	0.0625	0.1738	0.0000	1.4323
Δlog (Gas#93 wholesale price)	854	0.0409	0.0325	0.0000	0.2064
Δlog (Gas#97 wholesale price)	854	0.0416	0.0351	0.0000	0.2143
Δlog (GDP per capita)	1,604	0.6893	0.5250	0.0016	2.6764
Δlog (Population density)	1,539	0.4895	0.4290	0.0009	1.8431
Δlog (Average wage)	1,422	0.2021	0.1810	0.0001	1.1389
Δlog (Population)	1,680	0.7086	0.5405	0.0017	2.1276
Δlog (Passenger traffic by highway)	1,434	0.7663	0.5586	0.0006	3.2216

Note: The dispersion rates (in absolute values) for all variables are calculated with the same order which is randomly assigned. All monetary values are deflated in 2005 prices using province level CPI.

Table 4.7 The impact of Shell entry on the retail price dispersion for China (2001 - 2012)

VARIABLES	(1) Dispersion (Gas 90)	(2) Dispersion (Gas 90)	(3) Dispersion (Gas 90)	(4) Dispersion (Gas 93)	(5) Dispersion (Gas 93)	(6) Dispersion (Gas 93)	(7) Dispersion (Gas 97)	(8) Dispersion (Gas 97)	(9) Dispersion (Gas 97)
Treatment	0.0391***	0.0672**	0.0487	0.0525***	0.0094	-0.0103	0.0515***	0.0376	0.0266
	(0.0104)	(0.0337)	(0.0345)	(0.0142)	(0.0410)	(0.0411)	(0.0146)	(0.0388)	(0.0391)
Post0	0.0101***	0.0119***	0.0037	0.0034	0.0093***	0.0007	0.0028	0.0090***	0.0022
	(0.0034)	(0.0034)	(0.0040)	(0.0028)	(0.0032)	(0.0035)	(0.0028)	(0.0031)	(0.0035)
Treatment×Post0	-0.0091	-0.0076	0.0064	0.0039	0.0005	0.0125**	0.0056	0.0013	0.0149***
	(0.0061)	(0.0049)	(0.0062)	(0.0035)	(0.0037)	(0.0050)	(0.0036)	(0.0040)	(0.0052)
Post1			0.0118***			0.0172***			0.0125***
			(0.0041)			(0.0040)			(0.0038)
Treatment×Post1			-0.0085			-0.0153***			-0.0179***
			(0.0064)			(0.0054)			(0.0053)
Post2			0.0172***			0.0071			0.0055
			(0.0036)			(0.0042)			(0.0041)
Treatment×Post2			-0.0203***			-0.0029			-0.0029
			(0.0057)			(0.0054)			(0.0052)
ΔLog(GDP per capita)		0.0273***	0.0288***		-0.0149**	-0.0127		-0.0143**	-0.0126
		(0.0084)	(0.0083)		(0.0066)	(0.0066)		(0.0066)	(0.0066)
ΔLog(Population density)		0.0027	0.0077		0.0329	0.0382		0.0117	0.0150
		(0.0174)	(0.0180)		(0.0216)	(0.0219)		(0.0202)	(0.0205)
ΔLog(Average wage)		-0.0334	-0.0365**		-0.0564***	-0.0622***		-0.0522***	-0.0566***
		(0.0188)	(0.0186)		(0.0176)	(0.0175)		(0.0167)	(0.0167)
ΔLog(Population)		-0.0574***	-0.0574***		-0.0039	-0.0035		-0.0042	-0.0040
		(0.0181)	(0.0187)		(0.0187)	(0.0189)		(0.0169)	(0.0171)
ΔLog(Passenger traffic by highway)		-0.0100***	-0.0086**		-0.0025	-0.0013		0.0021	0.0027
		(0.0037)	(0.0037)		(0.0037)	(0.0037)		(0.0034)	(0.0034)
Constant	0.0082	0.0538**	0.0495**	0.0185***	0.0114	0.0062	0.0188***	0.0175	0.0150
	(0.0100)	(0.0209)	(0.0207)	(0.0070)	(0.0220)	(0.0222)	(0.0069)	(0.0200)	(0.0203)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,262	960	960	1,316	1,010	1,010	1,302	997	997
R-squared	0.5259	0.6636	0.6793	0.4743	0.5211	0.5377	0.4690	0.5158	0.5267

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Table 4.8 The impact of Shell entry on the retail price dispersion with subsamples (2001 - 2012)

VARIABLES	(1) East & Central Dispersion (Gas 90)	(2) East & Central Dispersion (Gas 93)	(3) East & Central Dispersion (Gas 97)	(4) West Dispersion (Gas 90)	(5) West Dispersion (Gas 93)	(6) West Dispersion (Gas 97)
Treatment	-0.0033	0.0315	0.0953***	0.0554***	-0.0777***	-0.0585***
	(0.0248)	(0.0274)	(0.0289)	(0.0210)	(0.0177)	(0.0184)
Post0	-0.0076***	-0.0094**	-0.0110**	-0.0001	0.0048	0.0100
	(0.0027)	(0.0043)	(0.0049)	(0.0056)	(0.0054)	(0.0053)
Treatment×Post0	0.0060	0.0063	0.0044	0.0131	0.0247***	0.0283***
	(0.0044)	(0.0051)	(0.0058)	(0.0099)	(0.0074)	(0.0071)
Post1	-0.0044	-0.0018	-0.0033	0.0266***	0.0229***	0.0164***
	(0.0034)	(0.0042)	(0.0047)	(0.0061)	(0.0059)	(0.0057)
Treatment×Post1	0.0190***	-0.0043	-0.0060	-0.0327***	-0.0183**	-0.0239***
	(0.0060)	(0.0046)	(0.0048)	(0.0103)	(0.0085)	(0.0079)
Post2	0.0046	0.0064	0.0076	0.0304***	0.0115**	0.0085
	(0.0033)	(0.0039)	(0.0040)	(0.0052)	(0.0057)	(0.0056)
Treatment×Post2	-0.0154**	-0.0136**	-0.0094	-0.0201***	0.0001	0.0000
	(0.0068)	(0.0058)	(0.0055)	(0.0077)	(0.0073)	(0.0072)
ΔLog(GDP per capita)	0.0056	-0.0095	-0.0148***	0.0431***	-0.0186	-0.0140
	(0.0051)	(0.0058)	(0.0056)	(0.0118)	(0.0096)	(0.0098)
ΔLog(Population density)	0.0230	0.0082	-0.0325	0.0157	0.0691**	0.0564**
	(0.0172)	(0.0189)	(0.0192)	(0.0257)	(0.0291)	(0.0265)
ΔLog(Average wage)	-0.0026	-0.0311**	-0.0223	-0.0754***	-0.0732***	-0.0654***
	(0.0126)	(0.0143)	(0.0150)	(0.0271)	(0.0246)	(0.0233)
ΔLog(Population)	-0.0345***	-0.0231**	-0.0244**	-0.1053***	-0.0240	-0.0250
	(0.0111)	(0.0097)	(0.0095)	(0.0266)	(0.0285)	(0.0251)
ΔLog(Passenger traffic by highway)	-0.0058**	0.0004	0.0095***	-0.0118**	-0.0037	-0.0021
	(0.0027)	(0.0031)	(0.0028)	(0.0051)	(0.0050)	(0.0046)
Constant	0.0592***	0.0546***	0.0492***	0.0754***	0.0013	0.0052
	(0.0131)	(0.0134)	(0.0128)	(0.0284)	(0.0296)	(0.0264)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	340	368	360	620	642	637
R-squared	0.7121	0.7240	0.7382	0.6932	0.5487	0.5272

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Table 4.9 The competitive impact of Shell entry on the retail price (2001 - 2012)

VARIABLES	(1) Overall (Gas 90)	(2) Overall (Gas 93)	(3) Overall (Gas 97)	(4) West (Gas 90)	(5) West (Gas 93)	(6) West (Gas 97)
Competition0	-0.0141	-0.0418***	-0.0495***	-0.0021	-0.0474***	-0.0549***
	(0.0136)	(0.0114)	(0.0132)	(0.0158)	(0.0124)	(0.0139)
Competition1	0.0033	0.0239**	0.0316**	0.0040	0.0206	0.0295**
	(0.0155)	(0.0107)	(0.0148)	(0.0145)	(0.0105)	(0.0144)
Competition2	0.0109	0.0029	0.0075	0.0009	0.0041	0.0060
	(0.0144)	(0.0107)	(0.0130)	(0.0148)	(0.0087)	(0.0113)
Log(GDP per capita)	-0.0111	0.0199	-0.0129	-0.0234	0.0256	-0.0114
	(0.0136)	(0.0114)	(0.0132)	(0.0206)	(0.0183)	(0.0219)
Log(Population density)	0.0751**	0.1136***	0.0782**	0.0963	0.1003	0.0579
	(0.0373)	(0.0393)	(0.0394)	(0.0550)	(0.0524)	(0.0518)
Log(Average wage)	0.0180	0.0394	0.0291	-0.0804	0.0343	0.0559
	(0.0316)	(0.0320)	(0.0322)	(0.0481)	(0.0476)	(0.0491)
Log(Population)	0.0464	0.0190	-0.0400	0.1275***	0.0455	-0.0353
	(0.0394)	(0.0333)	(0.0337)	(0.0298)	(0.0327)	(0.0418)
Log(Passenger traffic by highway)	0.0041	0.0011	0.0042	-0.0041	0.0064	0.0078
	(0.0048)	(0.0046)	(0.0047)	(0.0062)	(0.0055)	(0.0057)
Constant	7.6710***	7.1059***	8.2654***	8.1957***	7.0683***	8.0956***
	(0.5107)	(0.5066)	(0.5054)	(0.6430)	(0.6617)	(0.6855)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	444	458	455	264	269	268
R-squared	0.9903	0.9893	0.9890	0.9890	0.9876	0.9870

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Table 4.10 The impact of Shell entry on the wholesale price dispersion for China (2001 - 2012)

VARIABLES	(1) Dispersion (Gas 90)	(2) Dispersion (Gas 90)	(3) Dispersion (Gas 90)	(4) Dispersion (Gas 93)	(5) Dispersion (Gas 93)	(6) Dispersion (Gas 93)	(7) Dispersion (Gas 97)	(8) Dispersion (Gas 97)	(9) Dispersion (Gas 97)
Treatment	0.0404	-0.2975	-0.3314	0.0588***	0.0103	0.0123	0.0787***	0.0025	0.0238
	(0.0596)	(0.1925)	(0.1969)	(0.0166)	(0.0350)	(0.0358)	(0.0180)	(0.0314)	(0.0319)
Post0	-0.1201***	-0.1218***	-0.0849***	-0.0189***	-0.0165***	-0.0133**	-0.0252***	-0.0207***	-0.0153***
	(0.0265)	(0.0283)	(0.0274)	(0.0034)	(0.0042)	(0.0053)	(0.0036)	(0.0044)	(0.0054)
Treatment×Post0	0.0333	0.0367	0.0500	0.0024	0.0034	0.0034	0.0111**	0.0128**	0.0193**
	(0.0288)	(0.0408)	(0.0477)	(0.0052)	(0.0058)	(0.0077)	(0.0056)	(0.0061)	(0.0077)
Post1			-0.0767***			-0.0064			-0.0112**
			(0.0257)			(0.0053)			(0.0050)
Treatment×Post1			-0.0048			0.0034			-0.0062
			(0.0363)			(0.0077)			(0.0068)
Post2			0.0987***			0.0089**			0.0065
			(0.0275)			(0.0042)			(0.0040)
Treatment×Post2			-0.0154			-0.0083			-0.0108**
			(0.0283)			(0.0057)			(0.0051)
ΔLog(GDP per capita)		-0.2044***	-0.2052***		-0.0015	-0.0031		0.0020	-0.0020
		(0.0548)	(0.0547)		(0.0096)	(0.0098)		(0.0091)	(0.0091)
ΔLog(Population density)		-0.0030	-0.0149		-0.0158	-0.0171		-0.0015	-0.0050
		(0.0875)	(0.0886)		(0.0171)	(0.0171)		(0.0160)	(0.0156)
ΔLog(Average wage)		0.6927***	0.6567***		0.0479***	0.0442**		0.0465**	0.0403**
		(0.1492)	(0.1443)		(0.0181)	(0.0183)		(0.0188)	(0.0187)
ΔLog(Population)		-0.0817	-0.1005		-0.0267	-0.0277		-0.0183	-0.0215
		(0.0953)	(0.0969)		(0.0213)	(0.0214)		(0.0188)	(0.0190)
ΔLog(Passenger traffic by highway)		-0.0156	-0.0068		-0.0042	-0.0037		-0.0017	-0.0015
		(0.0268)	(0.0277)		(0.0041)	(0.0042)		(0.0038)	(0.0038)
Constant	0.0505**	0.1343	0.1428	0.0319***	0.0628***	0.0639***	0.0336***	0.0410**	0.0472**
	(0.0248)	(0.0956)	(0.0995)	(0.0080)	(0.0226)	(0.0225)	(0.0075)	(0.0206)	(0.0205)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,116	888	888	854	651	651	854	651	651
R-squared	0.3122	0.3881	0.4033	0.5552	0.4604	0.4649	0.6414	0.5667	0.5763

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Table 4.11 The impact of Shell entry on the wholesale price dispersion with subsamples (2001 - 2012)

VARIABLES	(1) East & Central Dispersion (Gas 90)	(2) East & Central Dispersion (Gas 93)	(3) East & Central Dispersion (Gas 97)	(4) West Dispersion (Gas 90)	(5) West Dispersion (Gas 93)	(6) West Dispersion (Gas 97)
Treatment	-0.4845	0.0713	0.0955	-0.1364	0.0131	0.0323
	(0.3052)	(0.0907)	(0.0772)	(0.0928)	(0.0188)	(0.0182)
Post0	-0.2151***	-0.0085	-0.0156**	-0.0457*	-0.0174**	-0.0144**
	(0.0633)	(0.0080)	(0.0078)	(0.0276)	(0.0078)	(0.0073)
Treatment×Post0	0.1087	0.0063	0.0065	0.0582	-0.0016	0.0280**
	(0.0907)	(0.0094)	(0.0083)	(0.0440)	(0.0117)	(0.0120)
Post1	0.0294	-0.0031	-0.0101	-0.0930**	-0.0057	-0.0100
	(0.0430)	(0.0100)	(0.0082)	(0.0402)	(0.0080)	(0.0071)
Treatment×Post1	-0.0372	-0.0127	-0.0109	-0.0094	0.0132	-0.0087
	(0.0647)	(0.0120)	(0.0080)	(0.0282)	(0.0114)	(0.0110)
Post2	-0.0478	0.0043	0.0039	0.1362***	0.0113	0.0121**
	(0.0411)	(0.0094)	(0.0077)	(0.0449)	(0.0057)	(0.0060)
Treatment×Post2	-0.0569	0.0086	0.0030	-0.0286	-0.0100	-0.0125**
	(0.0701)	(0.0144)	(0.0084)	(0.0198)	(0.0064)	(0.0060)
ΔLog(GDP per capita)	-0.2889***	-0.0098	-0.0118	-0.1846**	0.0034	0.0070
	(0.0999)	(0.0145)	(0.0107)	(0.0717)	(0.0145)	(0.0154)
ΔLog(Population density)	0.0359	-0.0492	-0.0468	0.0548	-0.0104	0.0006
	(0.1867)	(0.0624)	(0.0534)	(0.0789)	(0.0174)	(0.0159)
ΔLog(Average wage)	1.1588***	-0.0495	-0.0338	0.2875	0.0590***	0.0555**
	(0.2489)	(0.0356)	(0.0321)	(0.1493)	(0.0218)	(0.0228)
ΔLog(Population)	-0.3842**	-0.0328	-0.0196	0.0827	-0.0323	-0.0439
	(0.1661)	(0.0293)	(0.0248)	(0.1309)	(0.0292)	(0.0271)
ΔLog(Passenger traffic by highway)	0.0248	0.0003	0.0115	-0.0442	-0.0052	-0.0053
	(0.0536)	(0.0085)	(0.0076)	(0.0259)	(0.0048)	(0.0044)
Constant	0.6920***	0.0739**	0.0590**	0.1018	0.0617**	0.0570**
	(0.1979)	(0.0367)	(0.0296)	(0.0924)	(0.0256)	(0.0236)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	340	215	215	548	436	436
R-squared	0.5173	0.5262	0.7116	0.3696	0.4800	0.5398

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Table 4.12 The competitive impact of Shell entry on the wholesale price (2001 - 2012)

VARIABLES	(1) Overall (Gas 90)	(2) Overall (Gas 93)	(3) Overall (Gas 97)	(4) West (Gas 90)	(5) West (Gas 93)	(6) West (Gas 97)
Competition0	-0.0065	-0.0193	-0.0552***	-0.0079	-0.0143	-0.0510***
	(0.0152)	(0.0105)	(0.0091)	(0.0151)	(0.0128)	(0.0107)
Competition1	0.0152	0.0062	0.0265***	0.0116	0.0081	0.0248**
	(0.0232)	(0.0117)	(0.0101)	(0.0240)	(0.0126)	(0.0111)
Competition2	-0.0032	0.0086	0.0169**	-0.0131	0.0159	0.0206**
	(0.0219)	(0.0101)	(0.0081)	(0.0226)	(0.0095)	(0.0083)
Log(GDP per capita)	0.0162	0.0003	-0.0063	0.0282	-0.0105	-0.0010
	(0.0207)	(0.0181)	(0.0204)	(0.0346)	(0.0260)	(0.0329)
Log(Population density)	0.0301***	0.0226**	0.0257***	0.0289***	0.0093	0.0140
	(0.0093)	(0.0098)	(0.0092)	(0.0102)	(0.0086)	(0.0088)
Log(Average wage)	-0.0391	-0.0357	-0.0484	-0.0854	-0.0309	-0.0849**
	(0.0299)	(0.0289)	(0.0281)	(0.0443)	(0.0334)	(0.0328)
Log(Population)	0.0946	0.0318	0.0070	0.1563***	0.0123	-0.0012
	(0.0485)	(0.0377)	(0.0328)	(0.0436)	(0.0411)	(0.0383)
Log(Passenger traffic by highway)	-0.0001	0.0115***	0.0108***	0.0112	0.0130	0.0163**
	(0.0064)	(0.0038)	(0.0040)	(0.0065)	(0.0077)	(0.0065)
Constant	7.9145***	8.7449***	9.1903***	7.8055***	8.8938***	9.4450***
	(0.5253)	(0.4042)	(0.4160)	(0.6233)	(0.4150)	(0.4991)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	389	280	276	226	168	164
R-squared	0.9885	0.9694	0.9697	0.9883	0.9672	0.9679

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

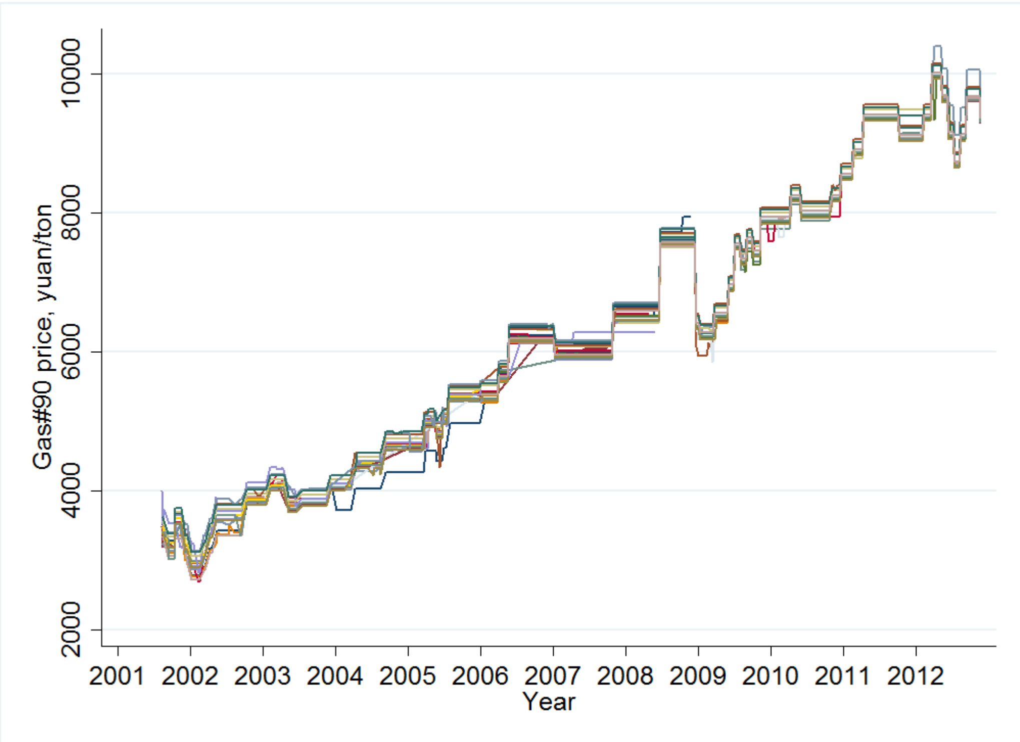
Table 4.13 The impact of foreign entry on the retail price dispersion for China (2001-2012 with four international retailers)

VARIABLES	(1) Dispersion (Gas 90)	(2) Dispersion (Gas 90)	(3) Dispersion (Gas 90)	(4) Dispersion (Gas 93)	(5) Dispersion (Gas 93)	(6) Dispersion (Gas 93)	(7) Dispersion (Gas 97)	(8) Dispersion (Gas 97)	(9) Dispersion (Gas 97)
Treatment	0.0243***	0.0525	0.0528	0.0598***	0.0793***	0.0767***	0.0519***	0.0868***	0.0841***
	(0.0063)	(0.0319)	(0.0314)	(0.0091)	(0.0260)	(0.0258)	(0.0086)	(0.0255)	(0.0253)
Post0	0.0002	0.0017	0.0040**	0.0010	0.0030**	0.0024	0.0008	0.0028**	0.0014
	(0.0013)	(0.0014)	(0.0016)	(0.0014)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0015)
Treatment×Post0	-0.0042	-0.0053**	-0.0026	-0.0027	-0.0015	0.0055	0.0013	0.0027	0.0115***
	(0.0022)	(0.0022)	(0.0027)	(0.0027)	(0.0028)	(0.0033)	(0.0026)	(0.0027)	(0.0033)
Post1			-0.0052***			0.0001			0.0014
			(0.0015)			(0.0013)			(0.0013)
Treatment×Post1			-0.0053**			-0.0116***			-0.0132***
			(0.0025)			(0.0028)			(0.0030)
Post2			-0.0001			-0.0010			-0.0017
			(0.0012)			(0.0012)			(0.0012)
Treatment×Post2			0.0027			0.0029			0.0017
			(0.0020)			(0.0020)			(0.0019)
ΔLog(GDP per capita)		0.0003	-0.0000		0.0031	0.0032		0.0012	0.0014
		(0.0029)	(0.0029)		(0.0028)	(0.0028)		(0.0029)	(0.0029)
ΔLog(Population density)		0.0099	0.0100		0.0206***	0.0204***		0.0197***	0.0196***
		(0.0084)	(0.0084)		(0.0067)	(0.0067)		(0.0061)	(0.0061)
ΔLog(Average wage)		-0.0085	-0.0086		-0.0116**	-0.0117**		-0.0114	-0.0116**
		(0.0067)	(0.0067)		(0.0054)	(0.0054)		(0.0059)	(0.0058)
ΔLog(Population)		-0.0185	-0.0171		-0.0236	-0.0195		-0.0331**	-0.0281
		(0.0175)	(0.0174)		(0.0148)	(0.0147)		(0.0146)	(0.0146)
ΔLog(Passenger traffic by highway)		-0.0018	-0.0017		-0.0013	-0.0015		-0.0016	-0.0018
		(0.0013)	(0.0013)		(0.0011)	(0.0011)		(0.0011)	(0.0011)
Constant	0.0110***	0.0166	0.0167**	0.0043***	0.0088	0.0075	0.0051	0.0103	0.0086
	(0.0025)	(0.0085)	(0.0081)	(0.0015)	(0.0068)	(0.0068)	(0.0034)	(0.0066)	(0.0066)
Year specific effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual specific effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,364	2,928	2,928	3,165	2,740	2,740	3,158	2,734	2,734
R-squared	0.5586	0.5862	0.5902	0.6624	0.6844	0.6883	0.6703	0.6949	0.6996

Note: Robust standard errors are reported in parentheses. ***, ** denote significance at the 1% and 5% levels respectively.

Appendix C

Fig. C.1 The sport price trend of Gas#90 in China (2011-2013)



Note: Data source CPMC. The spot price shown in this figure is from the anonymous station no.1 in each of our sampled cities. Unit yuan/ton.

Table C.1 The competitive impact of foreign entry on the wholesale price (2001 - 2012)

Province	Gasoline production	Gasoline consumption	Deficit	No. of Stations
Liaoning	936.49	401.80	534.69	0
Shandong	688.31	469.09	219.21	89
Guangdong	454.93	731.21	-276.28	34
Heilongjiang	409.40	333.26	76.14	0
Shaanxi	407.18	190.63	216.55	290
Shanghai	263.64	290.61	-26.97	0
Zhejiang	262.16	409.29	-147.13	0
Gansu	255.09	78.39	176.70	0
Xinjiang	240.73	115.11	125.62	0
Hainan	239.11	38.45	200.66	0
Jiangsu	238.46	496.11	-257.65	0
Hebei	221.88	213.33	8.55	113
Beijing	196.31	267.75	-71.44	24
Hubei	185.70	400.88	-215.18	0
Jilin	165.95	125.32	40.64	0
Henan	159.91	221.12	-61.20	0
Tianjin	140.35	150.03	-9.68	70
Hunan	138.78	215.20	-76.42	0
Fujian	112.95	228.15	-115.20	0
Jiangxi	89.76	93.30	-3.54	0
Anhui	84.03	120.02	-35.99	0
Guangxi	63.80	167.45	-103.65	0
Ningxia	59.91	21.79	38.13	0
Inner Mongolia	39.47	202.50	-163.03	0
Sichuan	37.19	338.90	-301.71	153
Qinghai	29.97	20.01	9.95	0
Shanxi	2.01	162.71	-160.70	58
Chongqing	0.42	89.77	-89.35	37
Yunnan	0.02	159.16	-159.14	0
Tibet	.	.	.	0
Guizhou	.	94.61	.	0

Note: Data source from China Energy Statistical Yearbooks. Data for Tibet is not available. Values in 10,000 tons.

Table C.2 Summary for variable definitions and units

Variable	Definition	Unit
Gasoline price	Gasoline price for Gas#90, Gas#93 or Gas#97	Yuan/ton
GDP per capita	Per capital of Gross Domestic Product	Yuan/person
Population density	Population divided by land area	Person per square km
Average wage	Average wage of staff and workers	Yuan
Population	Total population at the end of the year	10,000 persons
Passenger traffic by highway	Passenger traffic by highway	10,000 persons

Note: All monetary values are deflated in 2005 prices using province level CPI.

Table C.3 Estimation of propensity scores with logit

Entry	Coef.	Std. Err.	z	P>|z|	95% Conf. Interval	
Log(GDP per capita)	-2.648	0.695	-3.810	0	-4.010	-1.287
Log(Population density)	2.751	0.530	5.190	0	1.713	3.789
Log(Average wage)	7.284	1.603	4.540	0	4.142	10.430
Log(Passenger traffic by highway)	-0.648	0.274	-2.360	0.018	-1.185	-0.110
Log(Gas 90)	-2.386	1.305	-1.830	0.067	-4.944	0.171
Constant	-39.840	9.830	-4.050	0	-59.100	-20.570
N	464					
Prob> χ^2	0.000					
Pseudo-R^2	0.219					

Note: All monetary values are deflated in 2005 prices using province level CPI.

Chapter 5

Energy Abundance, Trade and the Geographical Distribution of the Manufacturing Sector in China

Energy Abundance, Trade and the Geographical Distribution of the Manufacturing Sector in China

Abstract

The next decade will see pressing demands on China to deliver a low-carbon economy and address growing energy shortages. In this paper we identify the impact of energy resources on industry location, structure and trade patterns. Employing a pseudo-endowment approach, we measure energy abundance using three-dimensional input data at the province-sector-year level from 2003 to 2009. Our results suggest that energy abundance has a significant impact on industry location and trade patterns, especially for energy intensive sectors. Two impact channels are specified, namely the availability of natural resource reserves and regulation laxity. Further analysis suggests that both components play a role in determining the industry location and trade with OECD countries. Our results suggest that environmental and energy regulations can be used to shape China's industrial structure.

JEL: F10; Q40; R12

Keywords: Energy abundance; Industry distribution; Trade patterns

5.1 Introduction

Energy has long been recognized as one of the most important inputs into the industrial production process. However, the impact of energy prices and the abundance of energy resources on industry location is little researched. Growing pressure on countries to develop low-carbon and sustainable economies means that identifying the impact of energy resources on industry specialization is of interest to both academics and policy makers. The purpose of this paper is to investigate the impact of energy abundance on industry location and the subsequent trade flows of firms in those locations within China. More specifically, we investigate how a comparative advantage in energy abundance affects the geographical distribution of firms and how this affects trade with OECD countries.

The contribution of our paper is two-fold. First, we utilize a cost-minimizing micro-based approach to estimate a pseudo-endowment indicator to proxy province level energy abundance. This approach enables us to estimate energy abundance directly from input data despite the regionally heterogeneous industrial structure (Gerlagh and Mathys, 2011).[1] This helps us to overcome problems of data availability and reliability across space and time. For robustness we employ two additional measures of energy abundance which are derived from different data sources. Second, to better understand the mechanisms through which energy abundance affects industry distribution and trade, we decompose the pseudo-endowment indicator into two components, resource reserves and regulation laxity, and investigate their impacts individually.

After 30 years of rapid growth, China now plays a major role in the international economy. Taken together with its position as the world's largest energy consumer, it is important to understand the impact of energy abundance on industrial production. The previous decade

[1] A revised version of Gerlagh and Mathys (2011) has been published in Energy Journal, see Gerlagh et al. (2015)

has witnessed an increase in the energy and environmental related costs faced by Chinese manufacturing plants. Industrial electricity prices ranged from 510 to 930 yuan per MWh across Chinese provinces in 2012 which is 20% higher than the prices in 2006 (SDRC, 2016). It places Chinese manufacturers at a competitive disadvantage compared to some international competitors. The electricity price for energy-intensive large-scale consumers in China is considered as one of the highest of all major exporters (Ecofys et al., 2015) and hence, means that some sectors may be increasingly vulnerable to international competition.[2]

To briefly summary our results, we find that energy abundance has a significant impact on industry location and hence trade location, especially for energy intensive sectors. Provinces with a higher level of energy abundance tend to specialize in producing and exporting energy intensive products. On average, a one percentage point change in energy abundance yields an approximately 0.2% change in the share of industrial production. The energy effect is confirmed by two alternative measures of province level energy abundance, namely the energy self-sufficiency ratio and the industrial electricity price. A one percentage point rise in the energy self-sufficiency ratio and a one percentage point decrease in the industrial electricity price leads to an approximately 0.6% and 2.0% rise of production share for sectors with an average energy dependency, respectively. Further analysis reveals that both resource reserves and regulation laxity are important mechanisms by which energy abundance affects the distribution of industry and trade. Provinces with relatively rich resources and lax environmental controls produce and export more energy intensive goods. Finally, we consider the comparative advantage of energy abundance at both the local level and global level. Based on the data of export transactions to OECD countries, the impact of energy abundance remains significant for energy intensive sectors. We find that countries with higher

[2] According to an international comparison of electricity costs of energy intensive industries (Ecofys et al., 2015, Figure 1), China ranks in 7$^{\text{th}}$ place behind Canada, the U.S., France, Germany, the Netherlands and South Korea but above Denmark, the UK, Italy and Japan. When comparing electricity rates subject to small, medium and large manufacturing firms, U.S. has a cost advantage for all three types of consumers. The largest gap is between medium electricity consumers in two countries where the U.S. rates can be 34%-49% lower than that in China (BLS and Tractus, 2016).

industrial electricity prices import more energy intensive goods from China's more energy abundant provinces. The result confirms previous findings and contributes to the evidence for developing countries.

The remainder of the paper is organized as follows. Section 5.2 provides a comprehensive review of previous researches covering the decision of industry location and energy related investigation. Section 5.3 presents the econometrical methodology and derivations for the factor endowment and industry intensity. Section 5.4 describes the data we use and empirical results are provided in Section 5.5. Conclusion is presented in Section 5.6.

5.2 Literature Review

There is a growing literature that examines the impact of energy abundance on international trade. A recent strand of literature considers energy endowments as one input into the production function together with capital and labour. Multi-country studies include Mulatu et al. (2010) and Gerlagh and Mathys (2011) while country specific studies include Ederington and Minier (2003) and Levinson and Taylor (2008). The way that energy endowments are modelled varies from study to study, depending largely on the research question. Some develop indicators to measure environmental capacity or utilize policy dummies while others employ continuous variables such as energy prices or pollution taxes. Although the literature has verified the important role of energy resources and environmental regulation in production location and global trade patterns, these studies have tended to concentrate on developed countries and it is unclear whether the result holds for developing countries.

Understanding the industrial spatial distribution across countries or across regions within a country is of interest to both academics and policy makers. The workhorse in the literature is the theory of comparative advantage that emphasizes the role of factor endowments and argues that countries tend to produce goods that consume more resources of which they have an abundance. Ricardo (1817) developed the classical theory of comparative advantage and Heckscher, Ohlin and Samuelson (HOS) extended the Heckscher-Ohlin (HO) model in the middle of nineteenth century. Leontief (1953), in a study of U.S. trade flows, finds that against expectations, U.S. imports were more capital intensive than exports.

Subsequent studies relax key assumptions of the HO model (Davis et al., 1997; Davis and Weinstein, 2000; Hakura, 2001). Davis et al. (1997) examines the factor abundance theory by exploring both international and Japanese regional data. They find the Heckscher-Ohlin-Vanek (HOV) model performs poorly under the conventional restrictive assumptions. However, when the assumption of universal factor price equalization is relaxed, the modified model fits remarkably well. Early studies also assume that countries use the same technology in production. The neglect of technological difference is assumed to systematically underestimate factor endowment effect. By calculating the actual technology matrices based on data from manufacturing and non-manufacturing in ten rich OECD countries, Davis and Weinstein (2000) find that the factor endowment theory is well identified by the data. A substantial 38 to 49 percent of trade flows can be explained by the endowment effect.

Hakura (2001) departs from the two-country model and analyzes the impact of factor endowments between each country and the rest of the world. The result highlights the importance of technology differences. It is notable that many of the studies have drawn a conclusion that the industry location model tends to fit better with data from a limited country or region rather than a broad cross country studies as there are fewer distorting trade barriers (Davis et al., 1997; Kim, 1999; Hakura, 2001).[3]

Recent studies have been carried out that combine models of comparative advantage with New Economic Geography (NEG) theory (Midelfart et al., 2000; Romalis, 2004; Egger

[3] Based on the two-digit manufacturing data across the U.S. from year 1880 to 1987, Kim (1999) finds that factor endowments contribute definitively to the industry location and interregional trade patterns.

and Egger, 2005; Klein and Crafts, 2012). Midelfart et al. (2000) develop a econometric framework to estimate the industry location across countries including both factor endowments and geographical characteristics such as transport costs and spatial patterns of demand. Employing sectoral data from 14 EU countries during the period 1980 to 1997, the study demonstrates that the skilled labour and scientific inputs are the major determinants of industry location. Romalis (2004) introduces a multinational HO model with continuous goods including the impact from scale economies, production differentiation and transport costs. Two predictions are proved using trade data from the U.S. and the Asia "miracle" four countries: countries with a large share of production and trade in goods that use their abundant factors intensively; rapid growth of an industry is followed by the accumulation of factors that are used intensively in that industry. Egger and Egger (2005) examine bilateral processing trade patterns between 14 EU countries as a microcosm of global trade. By summarizing different strands of production location theories, they include four categories of covariates in the model covering market size, endowments, trade costs information and infrastructure variables. Thus, trade costs turn out to be the most important factor followed by infrastructure variables in affecting processing trade. Relative endowment levels which are represented by absolute difference in GDP per capital are important in affecting outward processing trade. Klein and Crafts (2012) take the degree of market availability into account and find that market access is a determinant of U.S. industrial location between 1880 and 1920. Factor endowments matters only in the late 19th century with the influence fading away gradually.

More recently, due to increasing concerns about levels of pollution and environmental degradation, a large and growing body of literature extends the comparative advantage theory to include energy and environmental restrictions (Ederington and Minier, 2003; Copeland and Taylor, 2004; Cole et al., 2005; Levinson and Taylor, 2008; Hanna, 2010). The argument is summarized as the Pollution Heaven Hypothesis (PHH) which argues that in response to increasing regulations, developed countries tend to transfer pollution-intensive or energy-intensive production overseas where environmental regulations are less stringent. Based on a small open economy setting, Copeland and Taylor (2004) show that strict environmental regulations affect production location and trade flows. With the emphasis of endogenous environmental policy, Ederington and Minier (2003) and Levinson and Taylor (2008) both find the significant impact of environmental regulations on U.S. trade patterns. Moreover, Cole et al. (2005) provide an alternative explanation for the minor impact of environmental regulations on trade and investment based on industrial characteristics. The fact that pollution intensive industries require a large amount of physical and human capital means that developing countries are less attractive as a target for relocation. From an outward foreign direct investment perspective, Hanna (2010) finds that multinational firms based in the U.S. have a strong incentive to transfer their assets (5.3 percent) and production (9 percent) aboard due to the impact of the Clean Air Act Amendments initially passed in 1970. Similar results are found in studies of the EU emission trading system.[4]

Studies that consider the impact of energy abundance on production location include, from a global perspective, Mulatu et al. (2010); Gerlagh and Mathys (2011); Sato and Dechezleprêtre (2015). Utilizing the Johnson-Neyman technique for conditional effects, Mulatu et al. (2010) analyzes data covering 16 manufacturing industries from 13 European countries and concludes that the pollution heaven effect is present. However, both environmental stringency and the pollution intensity of an industry matter since the effect of environmental regulation is only significant for heavily polluting industries. As for the magnitude, environmental regulations have a similar effect to other determinants of industry location such as agriculture, education and research and development (R&D) expenditure.

To further examine the role of energy endowments, Gerlagh and Mathys (2011) present a new approach by estimating factor endowments with input data. Using this approach, factor

[4] See Arlinghaus (2015) for a summary of the results of recent papers.

abundance can be measured independently of industry structure and thereby avoiding the weak proxy issue of environmental regulations. Their study focuses on 14 high income countries and corroborates the finding that energy abundant countries have a comparative advantage in energy intensive sectors. A recent study from Sato and Dechezleprêtre (2015) also confirms the energy effect from the global perspective by investigating the impact of asymmetric energy prices. The dataset used is comprehensive and includes bilateral trade transactions covering 62 sectors between 42 countries between 1996 and 2011 which counts for 62% of global commodity trade. Although the impact is statistically significant, the magnitude of the impact is very small and explains less than 0.01% of the variation in trade flows.

Other recent studies (e.g. Ben Kheder and Zugravu, 2012; Michielsen, 2013; Aldy and Pizer, 2015) also confirm the impact of energy endowments on production location at the sub-regional level within one country. Based on U.S. industry, Aldy and Pizer (2015) find that higher energy prices lead to a decline in production of between 3 to 4 percent among key energy-intensive sectors. One the demand side, consumption declines by 2 to 3 percent which implies that roughly 1 percent of production has been transferred overseas. Michielsen (2013) carries out an investigation across 50 US states based on different types of resources including coal, national gas, oil and hydropower. The effect of energy endowments on industry location is confirmed statistically and economically even through energy is considered as tradable within a country. For sectors that have the energy intensity above the average, he finds a 20 percent increase of industrial value added due to a one standard deviation increase of coal or natural gas endowment. Hydro-power and oil endowments are also found to have a direct impact on production when controlling for energy prices. Focusing on French firm-level outward investment, Ben Kheder and Zugravu (2012) validate the impact of environmental regulation on firms' location choice for developed countries, most of emerging economics and Central and Eastern European countries. While for developing countries and the Commonwealth of Independent States, they reach a contrary conclusion where a stricter environmental regulation seems attract more investment from French firms. Collectively, these studies outline the important role of energy endowment in production location and trade patterns, at least for high income countries and for energy intensive sectors.

To date, little evidence has been found to confirm the competitiveness effect of energy endowments on industry location in China. To our best knowledge, the only recent exceptions are studies from Batisse and Poncet (2004) and Grether et al. (2014). With a focus on local protectionism, Batisse and Poncet (2004) finds that natural resources only exert a minor impact on industry location across Chinese provinces between 1992 and 1997. Specifically, the natural resource level is measured by the weighted average output of three energy products, i.e. oil, coal and ferrous and non-ferrous minerals. Little significance for the effect of natural resources is found except for provinces with a low level of international openness. Grether et al. (2014) highlights the determinants of production location from both comparative advantage and new economic geography aspects. With a balanced panel covering 12 industries in 28 provinces from 1999 to 2009, determinants tested include three traditional input factors (capital stock, skilled labour and energy inputs) and new economic geography factors (market potential and supplier access). Energy abundance is measured by total energy production per worker as well as disaggregated energy productions including coal, oil and natural gas. A positive and significant correlation is found between the aggregated energy abundance and industrial production share, although different energy carriers are found to have contradictory impacts. In summary, these two studies are much more concerned with natural resource reserves measured by energy productions. Little is known about the impact of environmental and energy regulations on industry distribution in China. Furthermore, as one of the major energy inputs in production process, the availability of electricity and the corresponding impact on industry distribution has yet to be fully understood.

More broadly, several studies (Chen, 1996; Cheng and Stough, 2006; Dean et al., 2009; Lan et al., 2012) examine the regional determinants of inward foreign direct investment (FDI) in China which involves energy resources and environmental regulations. One early study from Chen (1996) looks at the provincial data from 1987 to 1991 and argues that foreign investors have taken advantage of abundant energy resources in Western China in spite of the inefficient resource allocation. To examine the location choices of Japanese manufacturing FDI across Chinese provinces, Cheng and Stough (2006) include yearly electricity generation over provincial industrial output as one of the independent variables to measure the energy scarcity in a province. They analyze FDI data from 764 Japanese affiliates during year 1997 to 2002 and conclude that there is no significant impact of energy scarcity level on Japanese FDI location. Furthermore, Dean et al. (2009) investigate the PHH in China with a sample of equity joints ventures investments during 1993 to 1996. The water pollution levy is employed to measure the environmental stringency and results vary based on the source country of investment and sectoral pollution intensity. Only investments in pollution intensive sectors from Hong Kong, Macao, and Taiwan are found to be attracted by weak environmental stringency. Lan et al. (2012) argues that human resources play a crucial role in delivering a Pollution Heaven effect across Chinese provinces. Human capital is measured by the average year of schooling of the population aged above 15. It turns out that provinces with lower schooling years tend to be more attractive to dirty FDI and vice versa.

5.3 Methodology

5.3.1 Estimation of energy abundance

One of the contributions of the paper is to develop a measure of energy abundance for Chinese provinces that is independent of a province's sectoral structure, which in part addresses the endogeneity concerns. More specifically, our measure is estimated from a firm's profit maximizing behavior and abstracted from provincial sector level input data. Another advantage of this identification strategy compared to proxies such as energy production and prices is that it provides us with a systematic and uniform estimator in order to measure energy's impact on industry location across space and time. Such an approach is particularly useful for developing country studies that are often subject to limited data availability and inconstant statistics across space and time. Our approach, developed by Midelfart et al. (2000) has also been used by Gerlagh and Mathys (2011) to estimate the factor abundance level for 14 high-income countries between 1970 and 1997.[5] Following Gerlagh and Mathys (2011), the aggregate output $Y_{i,s}$ for province i, sector s is given by:

$$Y_{i,s} = A_i B_s K_{i,s}^{\alpha_s} E_{i,s}^{\beta_s} L_{i,s}^{1-\alpha_s-\beta_s}$$

where $K_{i,s}$, $E_{i,s}$ and $L_{i,s}$ are capital, energy and labour inputs for sector s in province i respectively.[6] The parameters A_i and B_s indicate province and sectoral technical capabilities and α_s and β_s are production elasticities with respect to capital and energy.[7] Based on the production function, total profit are given by:

$$\begin{aligned} Total\ profit &= Total\ production - Total\ cost \\ &= A_i B_s K_{i,s}^{\alpha_s} E_{i,s}^{\beta_s} L_{i,s}^{1-\alpha_s-\beta_s} - (r_i K_{i,s} + v_i E_{i,s} + w_i L_{i,s}) \end{aligned}$$

where r_i, v_i and w_i represent the unit cost of capital, energy and labour respectively. To maximize profits, the first order conditions shows that in equilibrium, the relative input of factors depends on the relative factor scarcity (unit cost ratio) and the sectors' dependency

[5] See Midelfart et al. (2000) for details of the methodological approach.

[6] For convenience, the subscript t for time is omitted in this section. All variables are time variant unless noted otherwise.

[7] For simplicity's sake, we assume a constant return to scale for all sectors. In later estimations the impact of return to scale will be accounted as sector-specific year effects.

on the factor (elasticity ratio);

$$\begin{cases} ln(\frac{K_{i,s}}{L_{i,s}}) = -ln(\frac{r_i}{w_i}) + ln(\frac{\alpha_s}{1-\alpha_s-\beta_s}) \\ ln(\frac{E_{i,s}}{L_{i,s}}) = -ln(\frac{v_i}{w_i}) + ln(\frac{\beta_s}{1-\alpha_s-\beta_s}) \end{cases}$$

We use θ_i to indicate the factor abundance level in province i and π_s for sectoral dependency on the factor;

$$\begin{cases} ln(\frac{K_{i,s}}{L_{i,s}}) = \theta_{K,i} + \pi_{K,s} + \varepsilon_{K,i,s} \\ ln(\frac{E_{i,s}}{L_{i,s}}) = \theta_{E,i} + \pi_{E,s} + \varepsilon_{E,i,s} \end{cases}$$

Hence, the relative inputs are decided jointly by province and sectoral characteristics. By regressing relative inputs on province fixed effects and sectoral fixed effects, θ_i and π_s are the parameters of the dummy variables. The estimate $\theta_{E,i}$ represents the energy abundance normalized by labour abundance in province i which depends on natural resource endowments, policies to encourage or restrict low-carbon or high-carbon industries, subsidies and preferential taxation rates. We classify the impact sources into two categories, namely natural resource endowments and policy orientation. Given that coal accounts for more than 80% of China's primary energy consumption during our study period, we use provincial coal production in natural logs to capture the natural resource endowment level. By regressing estimated energy abundance on coal production and province fixed effects, the coefficient vector of dummy variables measures the average strength (laxity) of local energy-related policies during the sample period.

$$\theta_{E,i} = \gamma_0 + \gamma_1 Production_i + Laxity_i \times Dummy_i + \varepsilon_{E,i} \tag{5.1}$$

The estimate $Laxity_i$ is time invariant and endogenous since policies are not implemented randomly. Generally speaking, developed provinces tend to adopt stricter regulations and have a greater demand for better environmental conditions. Such endogeneity downwardly biases the estimation of the impact of energy abundance on industry location.

5.3.2 Measurement of industry location

To formally capture the industry location across provinces in China, we use the industrial value added of sector s in province i dividing the domestic total sectoral value added normalized by province level total industry value added.[8] It gives us a double relative production share $S_{i,s} = \frac{Y_{i,s}}{\sum_i Y_{i,s} \sum_s Y_{i,s}}$. The impact of factor abundance can be then formulated as follows:

$$lnS_{i,s} = \alpha + \sum_{f=1}^{F} \beta_f(\theta_{f,i} - \bar{\theta}_f)(\pi_{f,s} - \bar{\pi}_f) + \varepsilon_{i,s} \tag{5.2}$$

The coefficient β_f indicates the importance of each input (relative to labour) in determining the production share. $\bar{\theta}_f$ and $\bar{\pi}_f$ indicate the cut-off points that represent the neutral level of factor abundance and factor dependency.[9] More specifically, when provinces have an energy abundance of $\bar{\theta}_E$, firms are considered to be indifferent to locate there regardless of there energy dependency. Likewise, sectors with $\bar{\pi}_E$ are considered to be indifferent to energy scarcity and hence unlikely to take province level energy abundance into account when deciding their location. As a result, sectors that rely significantly on energy inputs will be attracted to provinces that are rich in natural resources and relatively less stringent environmental regulations. The share of production under this situation will be increasing. In other words, β_E is expected to be positive and significant.

[8]The same measure of industry location is used by Midelfart et al. (2000) and Gerlagh and Mathys (2011). In Mulatu et al. (2010) the regional population is used for normalization to eliminate the size effect. In later estimation, we include both time variant province fixed effect and time variant sector effect and the denominator of the share is inoperative literally.

[9]Appendix D provides a derivation of cut-off points.

5.3.3 Testable hypotheses

Following Gerlagh and Mathys (2011), we test three related hypotheses.

Hypothesis 1. Industry specialization: Provinces with relatively high energy abundance levels attract energy intensive sectors. In other words, the share of energy intensive sectors is higher in energy abundant provinces everything else equal. We examine the industrial value added share and the employment share. After rearranging, Equation 5.2 is transformed into the equation below

$$lnS_{i,s,t} = \alpha + \beta_1 \theta_{E,i,t} \pi_{E,s,t} + \phi_{i,t} + \eta_{s,t} + \varepsilon_{i,s,t} \tag{5.3}$$

The dependent variable is the double relative industrial value added (or employment) share of sector s in province i. Our main variable of interest is the interaction between the energy abundance of province i and the energy dependency of sector s. In addition, we include time variant province fixed effects and time variant sectoral fixed effects to capture unobserved provincial and sectoral characteristics respectively.

As mentioned in Section 5.3.1, energy abundance is a combination of sources that we classify into two categories, namely natural resource endowment and policy orientation. Thus, Equation 5.3 is expanded to the equation below:

$$lnS_{i,s,t} = \alpha + \beta_1 Production_{i,t} \pi_{E,s,t} + \beta_2 Laxity_i \pi_{E,s,t} + \phi_{i,t} + \eta_{s,t} + \varepsilon_{i,s,t}$$

Coal production is our proxy for the provincial resource reserves level and regulation laxity measures as the average energy-related regulation strength. Coefficients for both interaction terms are expected to be positive.

Hypothesis 2. Trade specialization: Provinces with relatively high energy abundance export more energy intensive goods. We test the impact of energy abundance on the distribution of trade flows across Chinese provinces. The dependent variable is the exports of sector *s* in province *i* over total exports of sector *s* and total exports of province *i*. We also consider net export share as a robustness check. Hence, the estimation equation is given by:

$$lnS^X_{i,s,t} = \alpha + \beta_1 \theta_{E,i,t} \pi_{E,s,t} + \phi_{i,t} + \eta_{s,t} + \varepsilon_{i,s,t}$$

$$lnS^X_{i,s,t} = \alpha + \beta_1 Production_{i,t} \pi_{E,s,t} + \beta_2 Laxity_i \pi_{E,s,t} + \phi_{i,t} + \eta_{s,t} + \varepsilon_{i,s,t}$$

Positive and significant coefficients on the interaction terms imply that energy availability is an important consideration when importers choose the origin of their imports. Provinces with relatively higher energy abundance are assumed to specialize in the production of energy intensive goods and correspondingly have a comparative advantage in exporting energy intensive goods.

Since the energy abundance indicator reflects variation at the province level, no comparison is made between domestic and foreign trade partners. Previous studies demonstrate that countries with strict environmental regulations and costly energy prices tend to transfer domestic polluting industries to, or import more polluting products from, developing countries that usually have less strict environmental regulations (Ederington and Minier, 2003; Ederington et al., 2005; Hanna, 2010; Sato and Dechezleprêtre, 2015). To investigate the impact of energy on trade patterns, we collect the industrial electricity prices of 32 OECD countries and construct a triple interaction term. Trade flows are identified by sector, province, destination and time period. More specifically, industrial electricity prices are considered as a measure of energy abundance in destination countries. The competitive advantage of provinces with abundant energy is expected to be more obvious when facing trade partners with relatively high energy or environmental costs which leads to our third hypothesis.

Hypothesis 3: Provinces with relatively high energy abundance export more energy intensive goods to countries with relatively high energy costs. The estimation equation is given by:

$$lnS^X_{i,s,d,t} = \alpha + \beta_1 \theta_{E,i,t}\pi_{E,s,t} + \beta_1 \theta_{E,i,t}\pi_{E,s,t} lnIEP_{d,t} + \lambda_{i,d} + \phi_{i,t} + \eta_{s,t} + \varepsilon_{i,s,t}$$

The subscripts *s*, *i* and *d* indicate the sector, original province and destination information of trade flows. $IEP_{d,t}$ is the industrial electricity price in the export destination countries.[10] As well as time variant province and sectoral fixed effects, we also include the province-country specific effects to take into account existing trade relationships. The energy abundance level are compared not only from the horizontal (between provinces) but also from the vertical (between China and destination countries).

5.4 Data Description

The creation of a comprehensive dataset of inputs is essential for the estimation of energy abundance and energy dependency. Capital, energy and labour are considered as factor inputs into a firm's production process. Province-sector input data are collected from annual province statistical yearbooks. We also measure the energy abundance using two alternative proxies collected from different sources. The first proxy is the energy self-sufficiency ratio defined as province electricity production over electricity consumption. Both production and consumption data are from province energy balance sheets. The second proxy is the industrial electricity price of 36 large and medium cities collected from the Price Monitoring Center under the State Development and Reform Commission (SDRC 2016). Most of these 36 large and medium sized cities are capital cities of provinces and we use them to represent

[10] Annual average industrial electricity prices of OECD countries can be found in Table D.1 in the appendix.

the province level electricity price. For provinces with two or more than two reported cities, we take the annual average.[11]

For the dependent variables, industrial value added and employment for province i sector s are from annual province statistical yearbooks. The trade data are obtained from the General Administration of Customs of China. We aggregate the transaction data per product type, export location and destination country when we focus on OECD countries.[12] A summary of definitions can be found in Table D.2 in the appendix. A summary of statistics are presented in Table 5.1. Xinjiang and Tibet are excluded from the sample due to incomplete industry records. Hainan province is also excluded because of a lack of industrial activity. Our final unbalanced panel covers 30 2-digit manufacturing sectors in 27 provinces for the period 2003 to 2009.

[Table 5.1 about here]

To give a brief overview of the industrial structure in China, Table 5.2 provides the sectoral average input information for each province. Jiangsu, Guangdong and Shandong are the three provinces that use the most energy and capital. Eastern provinces use more than central and western provinces. Table 5.3 shows the sectoral input information for each 2-digit manufacturing sector. As expected, manufacturing related to metal and chemicals production have the highest energy requirements.

[Table 5.2 about here]

[Table 5.3 about here]

[11]The 36 large and medium size cities include 31 province-equivalent municipalities or provincial capitals, and 5 large non-capital cities including Qingdao (Shandong province), Ningbo (Zhejiang province), Dalian (Liaoning province), Shenzhen (Guangdong province) and Xiamen (Fujian province). Due to the data availability, the industrial electricity price ranges from year 2006 to 2009 which is shorter than our main investigation period 2003 to 2009.

[12]The dataset provides detailed information about the transaction such as firm identification, trading time and the product type (8-digit HS code). We use concordances provided by Dean and Lovely (2010) and GTAP (2006) to convert Customs HS code to Chinese industrial classification code.

Finally, we calculate the production elasticities for our three inputs, i.e. capital, energy and labour. To address the measurement units problem we estimate the input data using beta coefficients to make the coefficient comparable. The estimation equation is then given by:

$$lnY_{i,s,t} = \alpha + \beta_1 lnK_{i,s,t} + \beta_2 lnE_{i,s,t} + \beta_3 lnL_{i,s,t} + \phi_i + \eta_s + \lambda_t + \varepsilon_{i,s,t}$$

Subscripts i and s are for provinces and sectors respectively. We include province and sectoral fixed effects. Table 5.4 presents the results. To exclude the impact of the financial crisis, column (2) presents a subsample regression for period between 2003 and 2007. At a glance, all our three inputs exhibit a positive and significant impacts on industrial value added. During our period, capital tends to be the most important factor. A one standard deviation increase in capital use leads to a 52.3% to 63.5% standard deviation increase in industrial value added holding other factors constant. Labour is the second most important factor. A one standard deviation change in labour inputs increases the value added by 20.3% to 28.3% standard deviation of the normalized value. Energy is statistically significant at the 1% level in both specifications a smaller coefficient compared to capital and labour. Our results are in line with Yang and He (2014) who study 29 two-digit manufacturing sectors in China during 1998 to 2007 and find the capital and labour elasticities as around 0.6 and 0.3 respectively.

[Table 5.4 about here]

5.5 Results

5.5.1 Estimation of energy abundance

Based on our methodology the time variant relative factor abundance θ_E, θ_K and factor intensity π_E, π_K are estimated using capital, energy and labour input data. Table 5.5 provides a descriptive summary of these estimators. Figure 5.1 complements Table 5.5 by presenting the relative positions of Chinese provinces regarding energy abundance levels. From the bottom, bars to the right means that the provinces have good access to energy either through rich resource reserves or lax environmental policies. Inner Mongolia, Sichuan, Guizhou, Qinghai and Shanxi are the top five energy abundant provinces relative to labour according to our estimates. Reassuringly, provinces with large positive energy abundance are generally rich in natural resources. For example, Shanxi and Inner Mongolia have been the largest coal producing provinces in China since 2000.[13] Sichuan also has hydropower reserves of up to 150 million kw which is second only to Tibet, and it also leads the country in the reserves in titanium, vanadium, calcium and fluorite etc. which are important inputs in many metal related industries.[14] On the other hand, the top of Figure 5.1 shows the provinces that have low energy inputs relative to labour. Bars to the left show that a province has limited energy accessibility. As the capital of China, Beijing has the strictest environmental regulations and restricts the production of heavy industry. Hence, Beijing has the highest percentage difference between tertiary and secondary production relative to GDP. During our period

[13]Although the coal consumption is falling in recent years, coal resources still remain an important energy source in China. In 2006, Shanxi province produced 581.42 million tons of coal which is the largest producer in China followed by Inner Mongolia with 297.60 tons of production. At the end of our period, Inner Mongolia surpassed Shanxi with the coal production 600.58 tons and became the largest coal production province (NBSC, 2016).

[14]See http://www.china.org.cn/e-xibu/2JI/3JI/sichuan/sichuan-ban.htm for a description of natural conditions of Sichuan province.

2003 to 2009, the annual average secondary industry production relative to GDP in Beijing is 24.90% and the percentage for the tertiary industry is 74.07% giving a gap of 49.17%.

[Table 5.5 about here]

[Figure 5.1 about here]

Table 5.6 presents energy abundance levels for each province as well as the annual average coal production and regulation laxity. Corresponding to Figure 5.1, Beijing has the lowest energy abundance and has the strictest energy and environmental controls. Shandong, Hebei, Tianjin, Fujian and Shanghai have similar levels of strict environmental controls but different resource reserves levels. As the political and cultural centre in China, Chinese central government has released a series of regulations and measures to promote industrial upgrading and the relocation of heavy industries out of Beijing.[15] Particular effort were made before the Beijing 2008 Summer Olympics when nearly 200 coking, steel and chemical enterprises were relocated to neighbouring provinces such as Hebei and Tianjin (Ramzy, 2014). Amongst the most well-known was the move of Shougang Group, the fourth largest steel & iron enterprise in China from 2006 to 2011. In contrast, Sichuan, Guizhou and Guangxi had relatively loose energy and environmental regulations over this period with laxity values of 1.63, 1.48 and 1.35 respectively. In Figures 5.2, 5.3 and 5.4 displaying the energy abundance we observe that eastern provinces tend to have stricter regulations compared to central and western provinces.

[Table 5.6 about here]

[Figures 5.2, 5.3, 5.4 about here]

[15]For example, regulations and measures include “Measures to promote the relocation of polluting and disturbing enterprises, and speed up industrial restructuring in Beijing (1999)”, “Beijing government’s implementation of the investment system reform from the State Council (2005)” and “Notice on regulating the polluting and disturbing enterprises in Beijing (2007)”

We also utilize two alternative proxies of province level energy abundance and investigate their correlations with θ_E. Table 5.7 presents the correlation matrix and all parameters are significant at the 1% level. Energy abundance is positively correlated with the self-sufficiency ratio and negatively correlated with industrial electricity prices. Table 5.8 presents the pooled OLS results between the three variables at the province-year level. Bootstrapped standard errors with 500 replications are adopted to account for the small sample size. The results confirm a significant correlation between θ_E and the two alternative measures. In columns (2) and (4) we control for year specific effects. Both of the specifications are significant and robust. A ten percentage point increase in the energy abundance increases the self-sufficiency ratio by approximately 2.62% and 3.13% respectively and the electricity price falls by 1.03% and 1.04%. We now test our three hypotheses using three energy abundance measures (θ_E, self-sufficiency ratio and industrial electricity price) as well as the two impact channels (resource reserves and regulation laxity).

[Table 5.7 about here]

[Table 5.8 about here]

5.5.2 Hypotheses testing

The theory of comparative advantage suggests that countries that differ in their level of resource endowments will export goods requiring intensive input of the abundant resource. In our case, provinces with abundant energy resources should have an advantage in producing and hence exporting goods that require intensive energy inputs. As a result, the share of energy intensive industries are expected to be higher in energy abundant provinces keeping all other conditions the same. The expectation is framed as Hypothesis 1. Table 5.9 presents the empirical results. The first four columns are based on the share of industrial value added in province i industry s. The remaining columns have the share of employment as the dependent variable. Province specific time effects and sector specific time effects are included in all specifications to account for time variant provincial and sectoral characteristics.[16] Standard errors are robust and clustered at the province-sector level allowing for intragroup correlation (Rogers, 1994).

[Table 5.9 about here]

At first glance, the results suggest a statistically significant impact of energy abundance on industrial location through all of our three energy abundance measurements from column (1) to (3) and column (5) to (7). The coefficients of the interaction constructed by θ_E and the sectoral energy dependency π_E range from 0.205 to 0.165. This implies a 10 percentage point change of θ_E gives an approximately 2 percentage point change in the local production share for sectors with π_K at unit value all other things equal. Due to the nature of interaction term, the overall impact of energy abundance on industrial location depends not only on the abundance level, but also on the sectoral dependency on energy resources. The larger the π_E, the greater the production share will change given to a certain change in θ_E. For example, Manufacture of Foods (2-digit CIC code 14) has an energy dependency as 1.416 and for Manufacture of Chemical Fibers (2-digit CIC code 28) it is 3.101. Hence, a ten percentage point increase of θ_E in a province will lead to an approximately $2 \times 1.416 = 2.8\%$ increase of the product share of food manufacturing and a $2 \times 3.101 = 0.62\%$ increase of the product share of chemical fibers manufacturing. On average, the impact of energy abundance on production share is approximately $2 \times 1.65 = 3.3\%$ as the mean value of energy dependency is equal to 1.65. Gerlagh and Mathys (2011) finds the impact coefficients on the interaction terms range from 0.728 to 0.753 for value added share and 0.429 to 0.450 for employment share. Hence, they find a stronger impact of energy resources on industry location than we do for China. One possible explanation for the difference is that the panel used by Gerlagh

[16] In this case, any variation at province-year level and sector-year level will be captured by dummies.

and Mathys (2011) includes 14 high-income countries where firms are able to more quickly adapt to changes in energy and environmental conditions when choosing where to locate. In addition, they only include 10 broad sectors many of which are energy intensive sectors such as construction, transportation, iron and steel. Hence, the coefficient is likely to be larger than estimations based on a wider range of manufacturing sectors.

When we consider the self-sufficiency ratio in column (2) and (6), a ten percentage point increase leads to a $5.92 \times 1.65 = 9.8\%$ to $6.36 \times 1.65 = 10.5\%$ increase of the production (employment) share for sectors that have an average dependency on energy inputs. [17] Estimations based on industrial electricity prices in column (3) and (7) yield the largest elasticities. A ten percentage point increase in the electricity leads to a $19.01 \times 1.65 = 31.4\%$ to $21.76 \times 1.65 = 35.9\%$ fall in the production (employment) share for the average energy dependent sectors all other things equal. Hence, for Manufacture of Foods and Manufacture of Chemical Fibres, this means a $19.01 \times 1.416 = 27\%$ and a $19.01 \times 3.101 = 59\%$ fall respectively. Intuitively, taking the mean value of industrial electricity prices as an example, a ten percentage point change is equal to a 69 yuan/MWh price increase. As a result, a 69 yuan/MWh industrial price increase will lead to a 27% fall of production share for food manufacturing and a 59% fall of production share for chemical fibres manufacturing all other things equal.

In columns (4) and (8) we present the results where we distinguish between resource reserves and regulation laxity. Both resource reserves and regulation laxity have a statistically significant impacts on the industry location. Hence, our results confirm Hypotheses 1 that energy abundance impacts industry location in China. The decomposition results suggest that both natural resource reserves and energy-related regulations are important determinants of

[17]Note that although many of the manufacturing sectors are labour intensive compared to energy inputs, and hence have an energy dependency π_E below the neutral level $\bar{\pi}_E$, the share of the production will still rise when the energy abundance increases in a province.

industry distribution across provinces. Provinces with rich coal resources or loose regulation controls are more attractive to energy intensive sectors.

Table 5.10 presents the results for our test of Hypothesis 2 which examines the impact of energy abundance on trade specialization. Results show that energy abundance has a smaller impact on trade flows. The self-sufficiency ratio and industrial electricity prices are significant at the 5% level and 1% level respectively although no significant correlation is found between θ_E and trade shares. The magnitude of both the self-sufficiency ratio elasticity and the industrial electricity price elasticity are smaller than those in Table 5.9. This result may be explained by the fact that the trade flows are jointly decided not only by the domestic economic conditions but also by the international trade environment. Results in columns (4) and (8) indicate that both resource reserves and regulation laxity remain significant determinants of the location of trade flows, but again, with smaller elasticities than those in Table 5.9 . Provinces with rich natural resources and loose regulation controls are attractive to energy intensive sectors from both a production and an export perspectives.

[Table 5.10 about here]

To better understand the impact of energy abundance on trade patterns, we investigate the energy impact on the bilateral trade patterns between China and OECD countries. Each transaction is identified by sector, province, destination and year information. As a reminder, Table D.1 in the appendix provides a list of OECD countries and the annual average industrial electricity prices (IEP).

[Table 5.11 about here]

Table 5.11 provides the estimation results considering both inter-region and inter-nation energy abundance. We start by asking whether provinces with abundant energy have an advantage in exports generally regardless of the product type. In columns (1) to (3), the dependent variable is the total exports from province i to country d. The insignificant coefficients on the interaction terms reveal that there is little evidence associating general trade flows and energy abundance, despite using three different measures of energy abundance. When we concentrate on energy intensive sectors, we find a highly significant triple interaction terms in column (4) to (5) which indicates a strong impact of energy abundance on the exports of energy intensive products. Our results suggest that countries with significant higher IEP are more cautious when choosing their overseas origin for energy intensive goods. More specifically, they import more energy intensive goods from provinces with either rich resource reserves or loose energy and environmental controls. Hence, the significant impact of energy on international trade flows only holds for goods that rely heavily on energy inputs relative to labour inputs. Comparing the results from Table 5.11 with those in Table 5.10, it can be seen that the impact of energy abundance is enhanced if the import country is energy-scarce. Our finding is in line with the conclusion that relative energy prices play a significant role in bilateral import flows, especially for energy intensive goods (Sato and Dechezleprêtre, 2015).[18]

To test the robustness of our findings, we run a series of regressions following the framework in Tables 5.9 to 5.11. As shown in Figure 5.1, it is apparent that Beijing has an extraordinarily low energy abundance level compared to other provinces. Hence, we exclude Beijing as a outlier from our sample and the sub-sample results are present in Table D.3 in the appendix. The first four columns are based on the dependent variable production share; Columns (5) to (8) are based on exports share and the last four columns are based on trade flows with OECD countries. Results are significant and consistent with previous findings in Tables 5.9 to 5.11. To limit possible endogeneity issues, we further conduct a robustness check using

[18]Sato and Dechezleprêtre (2015) find that on average a 10 percentage point increase in the relative energy price gap between two countries would induce a 0.2% increase in import flows. The impact is higher for energy intensive sector with the elasticity of 0.027%. Hence, a 4% increase in the price difference between the UK and India tends to increase the UK's import by approximately 0.1%. The impact is small in magnitude but significant statistically.

lagged explanatory variables.[19] Table D.4 presents the lagged identification. All our three energy abundance measures as well as two channels are lagged by one year considering the relatively short time period. The results are broadly similar to our previous findings in terms of both size and significance.

5.6 Conclusions

Although energy resources have long been recognized as an important input into the production function, whether it has a direct impact on industry location remains unclear. To date evidence has tended to focus on developed countries. Following two decades of rapid growth, China has since 2010 surpassed US and become the world's largest energy consumer. Under increasing pressure China has started to emphasize energy conservation and pollution reduction. Hence, understanding the factors that influence industry location is of first-order-importance for policy makers who are looking to develop instruments to address China's pollution concerns and its unbalanced industrial development.

This paper investigates the impact of energy abundance on industry location and trade in China. Using a pseudo-endowment method, we introduce a time variant indicator to measure province level energy abundance between 2003 and 2009. Three hypotheses are tested covering the aspects of industry specialization and trade specialization. Our results suggest that provinces with relatively higher energy abundance have a comparative advantage in producing energy intensive goods and hence have a higher production share and export share of energy intensive goods on average. Both resource reserves and energy-related regulation controls are important determinants of manufacturing sectors' distribution. In addition, based on trade with OECD countries, the energy effect on trade specialization is enhanced

[19] Using lagged identification enables us to reduce the correlation between the independent variable and the error term under some circumstance (Bellemare et al., 2017).

if the industrial electricity price in destination countries is higher. The results are robust to alternative measures of province level energy abundance and confirmed by further robustness checks.

Our findings confirm the conclusion made by early studies about the importance of energy inputs based on developed countries. Furthermore, our results emphasize the importance of regional heterogeneity in China and provide insights for energy studies for other developing countries such as India. Despite the well-developed nationwide electricity transmission and distribution network, natural resource endowments remain an important determinant of the structure of local manufacturing. Industrial upgrading is one solution. Energy and environmental related policies can be used as effective instruments to simulate industrial upgrading due to the apparent significant impact of regulation stringency. Although strict regulations induce higher production costs which means the elimination of production capacity, it may promote the development of new energy resources and environment friendly industries. In addition, efficiency improvement from production specialization can yield benefits to offset the increasing energy cost to some extent.

Figures and tables

Fig. 5.1 Relative energy abundance referring from the neutral level (2003-2009)

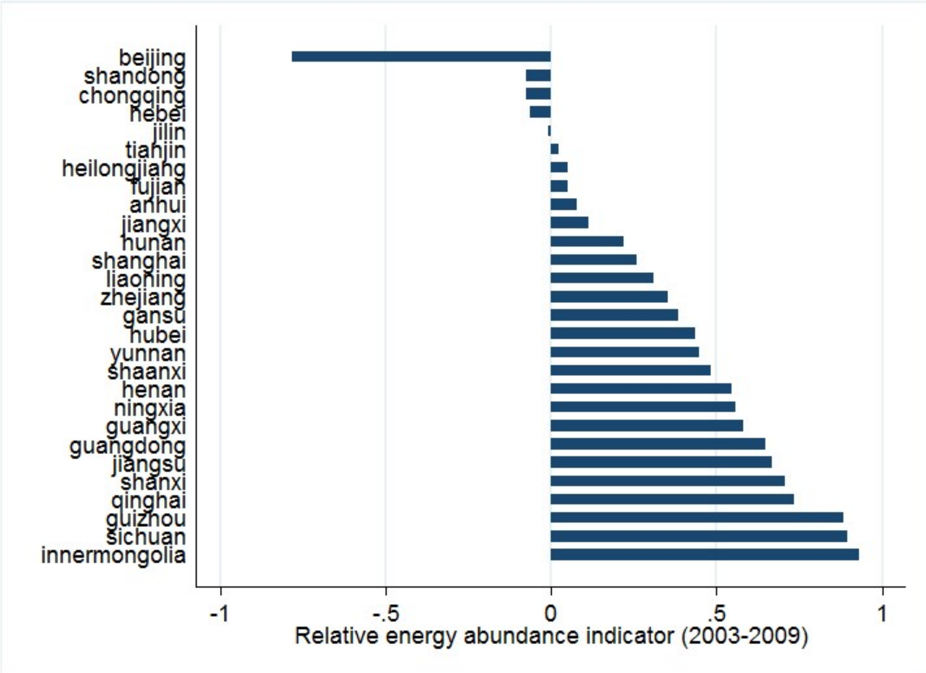


Fig. 5.2 Energy abundance footprint in China (2003-2009)

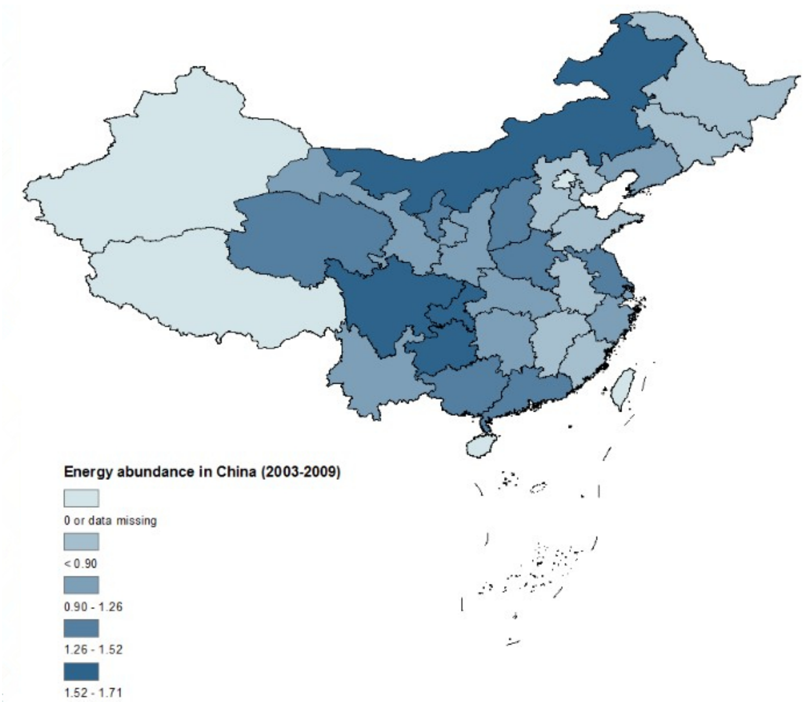


Fig. 5.3 Coal resource distribution in China (2003-2009)

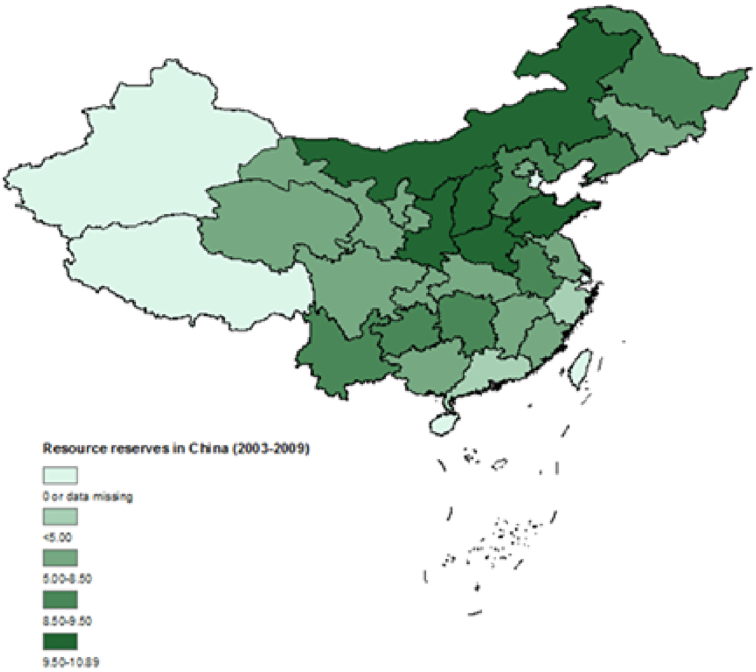


Fig. 5.4 Environmental regulation stringency in China (2003-2009)

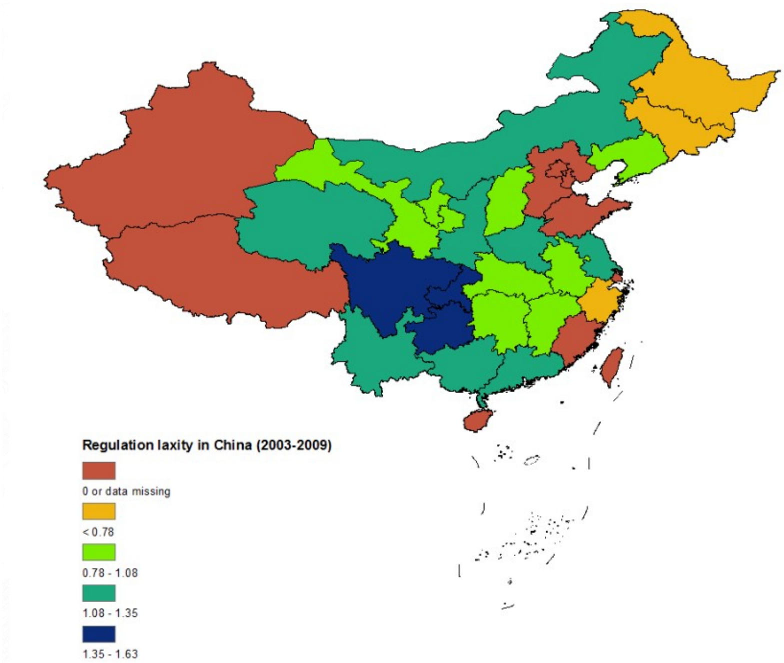


Table 5.1 Summary statistics (2003-2009)

Variable	Observations	Mean	S.D.	Min	Max
Capital	2,744	833,158	1,422,276	810	9,202,900
Energy	2,875	1,955,000	4,049,000	1,310	26,000,000
Labour	2,937	73,022	133,763	106	837,800
Industrial value added	2,937	833,502	1,485,000	662	9,274,400
Export	2,937	620,043	1,705,000	30.50	10,450,000
Self-sufficiency ratio	2,937	0.000	0.300	-1.000	0.600
Industrial electricity price	1,834	692	0.089	480	905
Coal production	2,669	9,793	14,067	12.300	63.021

Note: Data are summarized based on an unbalance panel of 30 manufacturing sectors in 27 Chinese provinces during the period from 2003 to 2009. The original trade data is in US dollar and we convert it into Chinese yuan based on annual exchange rate collected from NBSC website. The industrial electricity price covers the period from 2006 to 2009 due to data limitation. Monetary variables are deflated by Producer Price Index (PPI) at 2003 price. Table D.2 in the appendix presents variable definitions and units.

Table 5.2 Annual average capital, energy and labour inputs in China (2003-2009)

Province	Capital (10,000 yuan)	Energy (MWh)	Labour (Person)	West	Central	East
Jiangsu	2,667,041	5,839,673	227,428	0	0	1
Guangdong	2,374,794	5,071,886	279,581	0	0	1
Shandong	2,500,825	4,667,911	221,060	0	0	1
Zhejiang	1,959,558	4,592,201	220,934	0	0	1
Guizhou		3,213,941	16,670	1	0	0
Henan	937,274	2,874,143	102,599	0	1	0
Inner Mongolia	381,568	2,566,042	21,553	1	0	0
Sichuan	735,401	2,172,760	71,776	1	0	0
Hebei	946,000	2,070,070	79,876	0	0	1
Shanxi	668,438	2,051,073	41,198	0	1	0
Liaoning	1,314,786	2,048,726	63,386	0	0	1
Hubei	1,030,994	1,974,071	67,188	0	1	0
Hunan	569,637	1,670,709	52,384	0	1	0
Shanghai	1,511,412	1,610,034	87,469	0	0	1
Qinghai	139,668	1,447,933	4,835	1	0	0
Gansu	341,257	1,441,204	19,829	1	0	0
Fujian	708,487	1,418,248	93,106	0	0	1
Guangxi	383,678	1,390,929	28,950	1	0	0
Yunnan	319,508	1,352,469	19,185	1	0	0
Ningxia	156,867	1,247,761	7,024	1	0	0
Anhui	574,579	1,129,502	43,007	0	1	0
Shaanxi	411,436	1,005,844	31,126	1	0	0
Tianjin	571,063	907,672	37,119	0	0	1
Jiangxi	452,202	782,320	41,359	0	1	0
Chongqing	395,617	706,445	31,528	1	0	0
Heilongjiang	336,029	617,482	47,908	0	1	0
Jilin	486,185	612,394	28,153	0	1	0
Beijing	524,902	599,416	30,623	0	0	1

Note: Data source annual provincial statistic yearbooks. Capital data for Guizhou is missing for the whole period.

Table 5.3 Annual average relative inputs for manufacturing sectors in China (2003-2009)

CIC	Manufacturing industries	Capital relative to labour	Energy relative to labour
33	Smelting and processing of non-ferrous metals	32.30	197.16
32	Smelting and processing of ferrous metals	38.36	147.98
28	Manufacture of chemical fibres	23.78	133.77
26	Manufacture of chemical raw materials and chemical products	21.02	87.24
25	Processing of petroleum, coking, processing of nuclear fuel	49.35	77.06
42	Manufacture of artwork and other manufacturing	8.71	68.06
31	Manufacture of non-metallic mineral products	16.25	62.55
29	Manufacture of rubber	15.45	39.33
22	Manufacture of paper and paper prod.	16.66	37.31
43	Recycling and disposal of waste	12.23	35.46
34	Manufacture of metal products	10.48	30.92
30	Manufacture of plastics	12.49	27.52
27	Manufacture of medicines	15.46	24.95
20	Processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products	11.26	23.39
16	Manufacture of tobacco	40.79	22.45
24	Manufacture of articles for culture, education and sport activity	6.02	22.20
21	Manufacture of furniture	7.34	18.15
40	Manufacture of communication equipment, computers and other	14.26	17.84
19	Manufacture of leather, fur, feather and related products	5.87	16.76
41	Manufacture of measuring instruments and machinery for cultural activity and office work	8.75	16.51
13	Processing of food from agric. products	12.60	16.45
37	Manufacture of transport equipment	24.15	15.42
14	Manufacture of foods	12.17	14.55
15	Manufacture of beverages	18.13	14.45
17	Manufacture of textiles	7.41	13.42
23	Printing and recorded media	14.77	12.96
39	Manufacture of electrical machinery and equipment	9.98	12.44
35	Manufacture of general purpose machinery	8.41	11.26
18	Manufacture of textile, apparel, footwear, and caps	3.94	10.21
36	Manufacture of special purpose machinery	9.45	9.38

Note: Data source from annual provincial statistic yearbooks.

Table 5.4 Production elasticity estimation (2003-2009)

VARIABLES	(1) Industrial value added (2003-2009)	(2) Industrial value added (2003-2007)
Capital	0.523***	0.635***
	(0.040)	(0.035)
Energy	0.076***	0.051***
	(0.018)	(0.017)
Labour	0.283***	0.203***
	(0.031)	(0.025)
Observations	2,691	2,117
Adjusted R-squared	0.925	0.923

Note: Beta coefficients are reported in the table with robust standard errors in parentheses.

Table 5.5 Factor abundance and factor intensity (2003-2009)

Indicators	Mean	S.D.	Min	Max	Cutoff point
Energy abundance	1.088	0.528	-0.260	3.444	0.782
Capital abundance	0.800	0.357	-0.405	2.846	1.655
Energy intensity	1.649	0.982	-0.237	4.122	3.848
Capital intensity	1.384	0.636	-0.0231	2.957	2.376

Note: Indicators are estimated based on the methodology described in Section 5.3. The cutoff points represent the neutral level of factor abundance and factor intensity.

Table 5.6 Energy abundance and channels decomposition (2003-2009)

Province	Energy abundance	Coal production	Regulation laxity
Beijing	0.00	6.61	0.00
Shandong	0.71	9.57	0.00
Chongqing	0.71	8.19	0.76
Hebei	0.72	9.01	0.00
Jilin	0.77	8.03	0.71
Tianjin	0.81	0.00	0.00
Heilongjiang	0.83	9.11	0.75
Fujian	0.83	7.46	0.00
Anhui	0.86	9.12	0.87
Jiangxi	0.90	7.83	0.95
Hunan	1.00	8.58	1.02
Shanghai	1.04	0.00	0.00
Liaoning	1.09	8.78	0.93
Zhejiang	1.13	3.25	0.78
Gansu	1.17	8.22	0.96
Hubei	1.22	6.82	0.98
Yunnan	1.23	8.60	1.17
Shaanxi	1.26	9.75	1.12
Henan	1.33	9.82	1.21
Ningxia	1.34	8.20	0.98
Guangxi	1.36	6.35	1.35
Guangdong	1.43	4.98	1.23
Jiangsu	1.45	7.89	1.13
Shanxi	1.49	10.89	1.08
Qinghai	1.52	6.96	1.24
Guizhou	1.67	9.28	1.48
Sichuan	1.68	8.94	1.63
Inner Mongolia	10.34	8.63	1.25

Note: The estimation of energy abundance indicator is introduced in Section 5.3.1. Coal production data is collected from China Energy Statistics books and is at the annual average level in natural logs. Regulation laxity is estimated through Equation 5.2.

Table 5.7 Correlation matrix between energy abundance indicator, self-sufficiency ratio and industrial electricity price (2003-2009)

	Energy abundance indicator	Self-sufficiency ratio	Industrial electricity price
Energy abundance indicator	1		
Self-sufficiency ratio	0.620***	1	
Industrial electricity price	-0.221***	-0.181***	1

Table 5.8 Pooled OLS estimation of three energy abundance proxies (2003-2009)

	(1)	(2)	(3)	(4)
VARIABLES	Self-sufficiency ratio		Industrial electricity price	
Energy abundance	0.262***	0.313***	-0.104***	-0.103***
	(0.059)	(0.082)	(0.032)	(0.030)
Constant	-0.238***	-0.112	-0.269***	-0.325***
	(0.074)	(0.096)	(0.036)	(0.042)
Observations	145	145	100	100
Adjusted R-squared	0.244	0.259	0.096	0.159
Year specific effects	No	Yes	No	Yes

Note: Bootstrapped standard errors are reported in parentheses. Significant at *10%, **5%, ***1%.

Table 5.9 The impact of energy abundance on industry specification in China (2003-2009)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Share of IVA				Share of employment			
Interacted with energy dependency								
Energy abundance	0.205***				0.165**			
	(0.075)				(0.068)			
Self-sufficiency ratio		0.592***				0.636***		
		(0.161)				(0.122)		
Industrial electricity price			-1.901***				-2.176***	
			(0.343)				(0.360)	
Coal production				0.113***				0.139***
				(0.027)				(0.024)
Regulation laxity				0.279**				0.245***
				(0.110)				(0.092)
Constant	-4.574***	-3.661***	-4.061***	-3.924***	-4.213***	-3.173***	-3.989***	-3.546***
	(0.382)	(0.566)	(0.303)	(0.520)	(0.261)	(0.407)	(0.262)	(0.362)
Observations	2,937	2,937	1,834	2,669	2,937	2,937	1,834	2,669
Adjusted R-squared	0.622	0.631	0.664	0.637	0.570	0.585	0.615	0.605
No. of clusters	773	773	683	743	773	773	683	743
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the province-sector level are reported in parentheses. Significant at *10%, **5%, ***1%. Province specific year effects and sector specific year effect are included in all specifications. The time period for regressions including industrial electricity prices ranges from 2006 to 2009 due to data limitation.

Table 5.10 The impact of energy abundance on trade specification in China (2003-2009)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Share of export				Share of net export			
Interacted with energy dependency								
Energy abundance	0.065				0.246***			
	(0.056)				(0.076)			
Self-sufficiency ratio		0.202**				0.297***		
		(0.097)				(0.103)		
Industrial electricity price			-0.696***				-1.006***	
			(0.221)				(0.282)	
Coal production				0.058**				0.060**
				(0.025)				(0.025)
Regulation laxity				0.233**				0.240**
				(0.098)				(0.096)
Constant	-3.127***	-2.811***	-3.494***	-2.544***	11.864***	12.290***	12.347***	12.349***
	(0.282)	(0.354)	(0.259)	(0.410)	(0.510)	(0.488)	(0.439)	(0.570)
Observations	2,937	2,937	1,834	2,669	2,014	2,014	1,353	1,843
Adjusted R-squared	0.738	0.739	0.826	0.723	0.782	0.781	0.831	0.774
No. of clusters	773	773	683	743	658	658	592	633
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the province-sector level are reported in parentheses. Significant at *10%, **5%, ***1%. Province specific year effects and sector specific year effect are included in all specifications. The time period for regressions including industrial electricity prices ranges from 2006 to 2009 due to data limitation.

Table 5.11 The impact of energy abundance on exports to OECD countries (2003-2009)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Province exports to country *d*			Province exports of sector *s* to country *d*			
IEP × Energy abundance	0.058						
	(0.118)						
IEP × Self-sufficiency ratio		-0.186					
		(0.190)					
IEP × Industrial electricity price			-0.400				
			(0.399)				
IEP × Energy abundance × Energy dependency				0.013***			
				(0.004)			
IEP × Self-sufficiency ratio × Energy dependency					0.043***		
					(0.005)		
IEP × Industrial electricity price × Energy dependency						-0.018***	
						(0.004)	
IEP × Coal production × Energy dependency							0.008***
							(0.001)
IEP × Regulation laxity × Energy dependency							0.040***
							(0.005)
Constant	-8.545***	-8.461***	13.300	-17.149***	-17.156***	-8.402***	-16.974***
	(0.292)	(0.305)	(16.624)	(0.394)	(0.394)	(0.144)	(0.411)
Observations	3,874	3,874	2,795	82,906	82,906	62,394	72,396
Adjusted R-squared	0.878	0.878	0.893	0.636	0.636	0.681	0.602
No. of clusters	901	901	852	22758	22758	21442	20890
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year fixed effects	No	No	No	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors are reported in parentheses. Standard errors are clustered at the province-country level for the first three columns and at the province-sector-country level for the remaining columns. Significant at *10%, **5%, ***1%. Province specific year effects and country specific year effects are included in first three regressions. For the remaining columns country specific year effect is also included. The time period for regressions including industrial electricity prices ranges from 2006 to 2009 due to data limitation.

Appendix D

Derivation of cut-off points

In the paper we are interested in whether factor abundance plays an important role in determining industry location, or at least, for some specific sectors. The question can be expressed algebraically using the derivative relation below:

$$\frac{\partial lnS_{i,s}}{\partial \theta_{f,i}} = \beta_f(\pi_{f,s} - \bar{\pi}_f)$$

Hence, it is important to know the cut-off point and the relative position of each province with regard to their abundance level. To calculate the cut-off point, equation 5.2 is expanded as below:

$$lnS_{i,s} = \alpha' + \sum_{f=1}^{F} \beta_f \theta_{f,i} \pi_{f,s} + \sum_{f=1}^{F} \gamma_f \theta_{f,i} + \sum_{f=1}^{F} \delta_f \pi_{f,s} + \varepsilon_{i,s}$$

where

$$\alpha' = \alpha + \sum_{f=1}^{F} \beta_f \bar{\theta}_f \bar{\pi}_f$$

$$\gamma_f = -\beta_f \bar{\pi}_f$$

$$\delta_f = -\beta_f \bar{\theta}_f$$

Thus, cut-off points $\bar{\pi}_f$ and $\bar{\theta}_f$ can be calculated reversely.

Table D.1 Annual average IEP for OECD countries (2003-2009)

Country	Average price	Country	Average price
Norway	56.425	Greece	113.101
Canada	62.694	Germany	117.908
Korea	63.121	Turkey	121.249
United States	65.485	Portugal	124.465
New Zealand	66.116	Luxembourg	126.035
Estonia	82.057	Czech Republic	127.037
Sweden	84.607	United Kingdom	131.742
Switzerland	87.814	Slovenia	131.989
France	88.601	Austria	132.500
Finland	91.910	Japan	132.516
Israel	92.095	Chile	133.014
China	92.535	Netherlands	134.137
Poland	98.717	Belgium	138.693
OECD	98.896	Hungary	142.080
Spain	102.303	Slovak Republic	150.960
Mexico	103.164	Ireland	156.415
Denmark	109.524	Italy	253.120

Note: Data source from IEA Electricity Information 2012. Unit USD/MWh. Australia is not included due to missing values.

Table D.2 Variable definitions and units

Variable	Definition	Unit	Dimension
Capital input	Annual average of balance of net values of fixed assets	10,000 yuan	Province-industry-year
Energy input	Electricity consumption	MWh	Province-industry-year
Labour input	Annual average numbers of employment	Person	Province-industry-year
Industrial value added	Added value of industry	10,000 yuan	Province-industry-year
Employment	Annual average numbers of employment	Person	Province-industry-year
Exports	Export value from China Customs Statistics	10,000 yuan	Province-industry-year
Self-sufficiency ratio	Province electricity production over consumption		Province-year
Industry electricity price	Industrial electricity price 35kV and above	Yuan/MWh	Province-year
Industry electricity price of OECD countries	Industry electricity price of OECD countries	Yuan/MWh	Country-year

Table D.3 Robustness tests with the sample excluding Beijing (2003-2009)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		Share of IVA				Share of exports			Province exports of sector s to country d			
Interacted with energy dependency									*Interacted with energy dependency × IEP*			
Energy abundance	0.149**				0.062				0.012***			
	(0.070)				(0.071)				(0.004)			
Self-sufficiency ratio		0.909***				0.379*				0.062***		
		(0.201)				(0.202)				(0.007)		
Industrial electricity price			-1.856***				-0.706***				-0.018***	
			(0.345)				(0.223)				(0.004)	
Coal production				0.114***				0.066**				0.008***
				(0.027)				(0.026)				(0.001)
Regulation laxity				0.280**				0.325**				0.038***
				(0.117)				(0.132)				(0.006)
Constant	-3.186***	-3.225***	-3.696***	-5.153***	-2.908***	-2.924***	-3.158***	-4.914***	-17.162***	-17.169***	-7.938***	-13.041***
	(0.320)	(0.373)	(0.283)	(0.447)	(0.312)	(0.335)	(0.262)	(0.601)	(0.394)	(0.394)	(0.142)	(0.279)
Observations	2,761	2,761	1,717	2,493	2,761	2,761	1,717	2,493	78,650	78,650	59,359	68,140
Adjusted R-squared	0.634	0.644	0.679	0.651	0.738	0.739	0.827	0.722	0.637	0.637	0.682	0.600
No. of clusters	743	743	653	713	743	743	653	713	21825	21825	20543	19957
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Note: Clustered standard errors are reported in parentheses. Standard errors are clustered at the province-country level for the first six columns and at the province-sector-country level for the remaining columns. Significant at *10%, **5%, ***1%. Province specific year effects and country specific year effects are included in all regressions. For the last four columns country specific year effect is also included. The time period for regressions including industrial electricity prices ranges from 2006 to 2009 due to data limitation.

Table D.4 Robustness tests with lagged energy abundance variables (2003-2009)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		Share of IVA				Share of exports			Province exports of sector s to country d			
Interacted with energy dependency									*Interacted with energy dependency × IEP*			
Energy abundance$_{t-1}$	0.190**				0.046				0.009***			
	(0.085)				(0.061)				(0.003)			
Self-sufficiency ratio$_{t-1}$		0.594***				0.163*				0.039***		
		(0.177)				(0.096)				(0.005)		
Industrial electricity price$_{t-1}$			-1.740***				0.010				-0.022*	
			(0.381)				(0.140)				(0.013)	
Coal production$_{t-1}$				0.117***				0.049*				0.008***
				(0.028)				(0.025)				(0.001)
Regulation laxity$_{t-1}$				0.293**				0.221**				0.029***
				(0.132)				(0.110)				(0.003)
Constant	-4.605***	-3.900***	-3.767***	-4.064***	-3.168***	-2.969***	-3.564***	-2.741***	-12.383***	-17.156***	-8.105***	-17.180***
	(0.340)	(0.517)	(0.289)	(0.478)	(0.306)	(0.347)	(0.148)	(0.391)	(0.339)	(0.394)	(0.099)	(0.403)
Observations	2,208	2,208	1,207	1,999	2,208	2,208	1,207	1,999	66,202	77,106	49,093	67,865
Adjusted R-squared	0.624	0.634	0.664	0.640	0.756	0.756	0.887	0.733	0.653	0.647	0.713	0.611
No. of clusters	737	737	615	707	737	737	615	707	22109	22658	21114	20788
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year fixed effects	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Note: Clustered standard errors are reported in parentheses. Standard errors are clustered at the province-country level for the first six columns and at the province-sector-country level for the remaining columns. Significant at *10%, **5%, ***1%. Province specific year effects and country specific year effects are included in all regressions. For the last four columns country specific year effect is also included. The time period for regressions including industrial electricity prices ranges from 2006 to 2009 due to data limitation.

Chapter 6

Conclusions, Limitations and Future Research

6.1 Conclusions and Policy Implications

This thesis has presented four empirical studies with the aim of making an original contribution on the topic of energy economics in China. Following the first chapter laying the groundwork, the second chapter investigates the determinants of provincial energy intensity (energy consumed per unit of output) in China over the period 1995 to 2012. Special attention is paid to the role of urbanization. Through the recently developed mean group estimation technique, we find a positive direct impact of urbanization on energy intensity. However, the indirect impact of urbanization through four channels (construction, industrial upgrading, transportation and changing lifestyles) tend to be negative. The results highlight the difference between formal and informal urbanization.

In the third chapter we investigate how changes in energy prices affect manufacturing firms' product choices for the period 2005 to 2007. Employing an instrumental approach, our results suggest that higher electricity prices tend to promote surviving firms to adjust the 4-digit industry they operate in. More specifically, we find that higher energy costs provide an incentive for firms to switch to a less energy intensive industry, and to dampen a firm's desire to switch to a less energy intensive industry. Besides energy costs, we also find some significant firm-level characteristics and industrial characteristics that influence firms' switching decision.

Inspired by the global expansion of multinational retailing corporations, the fourth chapter investigates the entry effect of Royal Dutch Shell on China's retail and wholesale gasoline markets. Utilizing the propensity score matching method, each of the Shell populated city has been matched with three to five counterfactual cities that have similar possibilities to be populated by Shell in a specific year. Through the pair-wise approach, the absolute gasoline price differentials are calculated between any two matched cities for the purpose of measuring the market dispersion level. Our results from difference-in-difference method suggest that Shell's entry into Chinese gasoline market caused a significant degree of price dispersion in the first year of entry. The increased price dispersion is found to close again over the following two years. Highly refined gasoline products and the segmented market in Western China tend to be the most affected. Two potential mechanisms, the market-specific mechanism and the aggregation mechanism, explain the increase in the price dispersion.

The fifth chapter looks at the competitiveness impact of energy abundance on production distribution and trade patterns in China for 2-digit manufacturing sectors over the period 2003 to 2009. Energy abundance is measured by three indicators, the pseudo-endowment indicator estimated by a cost-minimizing approach, energy self-sufficiency ratio and industrial electricity prices. We find that the energy abundance level measured by all three indicators shows a consistent and significant impact on industrial distribution and hence trade location. The impact is mainly dominated by energy intensive sectors. Both resource reserves and regulation stringency are effective mechanisms by which the energy abundance level affects industry and trade distributions. Firms that rely heavily on energy inputs tend to cluster in regions with rich resource reserves and/or under relatively lax energy and environmental controls.

Taken together, the empirical findings in this thesis highlight several policy implications. First, the results in Chapter two emphasize a substantial difference between the formal urbanization and the informal urbanization in terms of influencing the efficiency of energy usage. Hukou system has played a crucial role in the formation of this substantial difference. Our results support the existing argument that migrants without urban hukou are perceived to receive unfair treatment in regard to the availability of public services and social welfare. Therefore, reforming or abolishing the hukou system should be an integral part of policies that promote the rural-urban transition and the development of sustainable society.

Second, our results in Chapter three and Chapter five suggest that energy policies including market-based pricing tools is prone to be effective in promoting industrial structure shifting and industry specialization, both of which are crucial to bolstering energy efficiency. However, there tends to be a gap between national plans and policy outcomes at the local level. Although environmental goals and policies at the national level are ambitious and comprehensive, insufficient and inconsistent local level implementation can hold back significant improvements in urban environmental quality. One way that may prevent the disparity is to assign a higher weight to environment protection in officials' performance evaluations. The prospect for career advancement may stimulate provincial and local officials to take environmental pollution as a serious concern. In fact, the environmental quality has been taken into account in the guidelines for cadre performance evaluation in several provinces.

Third, the findings in the fourth chapter suggest that opening up power sectors to foreign direct investment can enhance market competition to some extent. In recent years the government has consistently demonstrated its willingness to invest heavily in renewable energy and green technologies to resolve the pollution problem. Considering the existing ownership structure in conventional energy sectors, renewable energy sector may provide greater opportunities for foreign investments. Investment incentives and preferential policies shall be considered to support foreign investments as well as private investments.

6.2 Limitations

The major limitation of this thesis is the lack of detailed energy data in China. For example, in Chapter four when we study the market-specific mechanism, we construct a measure of the degree of competition from Shell based on the number of Shell stations in an individual market scaled by the maximum number of Shell stations in a city which is Xian with 113 stations. Ideally our Shell competitive index should be a time-variant variable and increase over time since the gasoline retail network is built up year by year. However, we only have the total number of stations located in a city and not the opening date for each individual station. Using the total number of stations at least provides us some insight to measure the competitive strength from Shell. Furthermore, the relatively short period of the panel data used in Chapter three when we study firms' switching behaviour adds further caution regarding the generalizability of the findings.

Our estimates may suffer from an inherent bias due to the endogeneity of energy and environmental policies. We hope that through econometric tools such as instrumental variable and propensity score matching, the results reflect reality. As we stated previously, there tends to be a gap between national plans and policy outcomes at the local level. This also leads to a difficulty of measuring the actual effect of energy and environmental restrictions at the local level.

We do acknowledge that using linear probably model for binary dependent variables may result in some estimation issues despite our remediations. The error terms may not be normally distributed, and there tends to be heteroskedasticity. The predicted values may fall outside the logical boundaries of 0 and 1. The selection of econometric techniques shall depend on many factors, such as the context of the core question and characteristics of the data. Presumably, one suitable technique for binary dependent variable with a large number of zeros is the robust weighted kernel logistic regression.

6.3 Future Research

The previous decade has witnessed an increase in the energy related costs faced by Europe manufacturing. The development in global energy markets, the EU Emissions Trading System (EU ETS), and the promotion of renewable energy sources put challenges in providing affordable energy for Europe manufacturing. Particularly, the long-term commitments of the EU and Germany to make their energy systems climate-neutral by 2050 will require additional investments and subsidies in the trillions. This will affect energy costs for manufactures unavoidably. Meanwhile, with the introduction of a national Emission Trading System and the coal-to-gas switching policy, an increase of energy costs is also expected for Chinese manufacturing firms. Further research could usefully investigate the impact of relative energy abundance between Germany and China on bilateral trade – both countries are among the world's largest economies and international trade plays a significant role in their economies. For the future development of domestic energy policies, it is important to understand the mechanisms through which domestic (China) and foreign (Germany) energy policies affect the bilateral trade relationship.

Furthermore, there are still many unanswered questions about firms' reactions to changing energy and environmental constraints. In particular, I am interested in the conditions under which firms will choose to (1) exit the market shortly, (2) stay in the original industry/location, (3) switch to another industry and produce another product (resources reallocation), (4) switch to another location (resource relocation) when facing more stringent energy and environmental constraints. Possible factors that influence the choice may include the type of energy and environmental constraints, levels of capital intensity and labour intensity, and the degree of industrial agglomeration. The results shall shed a light on avoiding undesired outcomes induced by energy and environmental policies.

Last but not least, I would be interested to explore how the increase of energy costs are shared between buyers and sellers. Currently two chapters study the energy usage from the producer side. Given the role of consumers and the demand side, very little is known about how increases in energy input costs are split between consumers and producers. Existing literature on carbon cost pass-through suggests that the power sector, as the most analyzed and largest regulated sector under the EU ETS, is able to pass a major part of the freely allocated allowances costs during the first two trading periods (2005-2012). According to the Theory of Incidence, the degree of pass-through of energy taxes from producers to consumers tends to be related to some key factors such as inputs substitution, returns to scale, market competition, and consumers' demand substitution. More information on energy usage at the firm level would help us to establish a greater degree of accuracy on this matter.

References

Abeberese, A. B. (2012). Electricity cost and firm performance: Evidence from India. *Department of Economics, Columbia University, New York.*

Abernathy, W. J. and Utterback, J. M. (1978). Patterns of industrial innovation. *Technology Review*, 64(7):254–228.

Agarwal, R. and Audretsch, D. B. (2001). Does entry size matter? The impact of the life cycle and technology on firm survival. *Journal of Industrial Economics*, 49(1):21–43.

Alam, M. (2013). Coping with blackouts: Power outages and firm choices. *Department of Economics, Yale University*.

Alby, P., Dethier, J.-J., and Straub, S. (2012). Firms operating under electricity constraints in developing countries. *World Bank Economic Review*.

Aldy, J. E. and Pizer, W. A. (2015). The competitiveness impacts of climate change mitigation policies. *Journal of the Association of Environmental and Resource Economists*, 2(4):565–595.

Allcott, H., Collard-Wexler, A., and O'Connell, S. D. (2016). How do electricity shortages affect industry? Evidence from India. *American Economic Review*, 106(3):587–624.

Apergis, N. and Payne, J. E. (2009). Energy consumption and economic growth in Central America: Evidence from a panel cointegration and error correction model. *Energy Economics*, 31(2):211–216.

Arlinghaus, J. (2015). Impacts of carbon prices on indicators of competitiveness. *OECD Environment Working Papers*.

Arnold, J. M. and Hussinger, K. (2005). Export behavior and firm productivity in German manufacturing: A firm-level analysis. *Review of World Economics*, 141(2):219–243.

Audretsch, D. B. (1991). New-firm survival and the technological regime. *Review of Economics and Statistics*, pages 441–450.

Audretsch, D. B. and Mahmood, T. (1995). New firm survival: new results using a hazard function. *Review of Economics and Statistics*, pages 97–103.

Baltagi, B. H., Bresson, G., and Pirotte, A. (2007). Panel unit root tests and spatial dependence. *Journal of Applied Econometrics*, 22(2):339–360.

Baser, O. (2006). Too much ado about propensity score models? Comparing methods of propensity score matching. *Value in Health*, 9(6):377–385.

Basker, E. (2005). Selling a cheaper mousetrap: Wal-mart's effect on retail prices. *Journal of Urban Economics*, 58(2):203–229.

Batisse, C. and Poncet, S. (2004). Protectionism and industry location in Chinese provinces. *Journal of Chinese Economic and Business Studies*, 2(2):133–154.

Bellemare, M. F., Masaki, T., and Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *Journal of Politics*, 79(3):000–000.

Ben Kheder, S. and Zugravu, N. (2012). Environmental regulation and French firms location abroad: An economic geography model in an international comparative study. *Ecological Economics*, 77:48–61.

Bernard, A. B., Jensen, J. B., Redding, S. J., and Schott, P. K. (2007). Firms in international trade. *Journal of Economic Perspectives*, 21(3):105–130.

Bernard, A. B., Redding, S. J., and Schott, P. K. (2006). Multi-product firms and trade liberalization. *National Bureau of Economic Research Working Papers*.

Bernardini, O. and Galli, R. (1993). Dematerialization : Long-term trends in the intensity of use of materials and energy. *Futures*, (May):3–14.

Berndt, E. R. and Wood, D. O. (1979). Engineering and econometric interpretations of energy-capital complementarity. *American Economic Review*, pages 342–354.

Bloch, H. and Wills-Johnson, N. (2010). The shape and frequency of Edgeworth price cycles in an Australian retail gasoline market. *SSRN:1558747*.

Blonigen, B. A. and Tomlin, K. (2001). Size and growth of Japanese plants in the United States. *International Journal of Industrial Organization*, 19(6):931–952.

BLS and Tractus (2016). A comparison of U.S.and China electricity costs. *Report for the German Ministry of Economic Affairs and Energy*.

Borenstein, S. and Rose, N. L. (1994). Competition and price dispersion in the US airline industry. *Journal of Political Economy*, 102(4):653–683.

Brandt, L., Van Biesebroeck, J., and Zhang, Y. (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics*, 97(2):339–351.

British Petroleum (2015). Statistical review of world energy.

Byrne, D. P. (2012). Petrol price cycles. *Australian Economic Review*, 45(4):497–506.

Byrne, D. P. and de Roos, N. (2017). Consumer search in retail gasoline markets. *Journal of Industrial Economics*, 65(1):183–193.

Byrne, D. P., Leslie, G. W., and Ware, R. (2013). How do consumers respond to gasoline price cycles? *SSRN:1903558*.

Cabral, L. (1995). Sunk costs, firm size and firm growth. *Journal of Industrial Economics*, pages 161–172.

Cabral, L. and Ross, T. W. (2008). Are sunk costs a barrier to entry? *Journal of Economics and Management Strategy*, 17(1):97–112.

Carr, J. C., Beatson, R. K., Cherrie, J. B., Mitchell, T. J., Fright, W. R., McCallum, B. C., and Evans, T. R. (2001). Reconstruction and representation of 3D objects with radial basis functions. In *Proceedings of the 28th annual conference on Computer graphics and interactive techniques*, pages 67–76. ACM.

Chang, S. J. and Xu, D. (2008). Spillovers and competition among foreign and local firms in China. *Strategic Management Journal*, 29(5):495–518.

Chen, C.-H. (1996). Regional determinants of foreign direct investment in mainland China. *Journal of Economic Studies*, 23(2):18–30.

Chen, J. (2011). China's experiment on the differential electricity pricing policy and the struggle for energy conservation. *Energy Policy*, 39(9):5076–5085.

Chen, Y., Ebenstein, A., Greenstone, M., and Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences*, 110(32):12936–12941.

Chen, Z. (2003). Dominant retailers and the countervailing-power hypothesis. *RAND Journal of Economics*, pages 612–625.

Cheng, S. and Stough, R. R. (2006). Location decisions of Japanese new manufacturing plants in China: A discrete-choice analysis. *Annals of Regional Science*, 40(2):369–387.

Cole, M. A. and Elliott, R. J. (2003). Determining the trade–environment composition effect: The role of capital, labor and environmental regulations. *Journal of Environmental Economics and Management*, 46(3):363–383.

Cole, M. A., Elliott, R. J., and Shimamoto, K. (2005). Why the grass is not always greener: The competing effects of environmental regulations and factor intensities on US specialization. *Ecological Economics*, 54(1):95–109.

Copeland, B. R. and Taylor, M. S. (2004). Trade, growth, and the environment. *Journal of Economic Literature*, 42(1):7–71.

Cropper, M. (2010). What are the health effects of air pollution in China? *International Economic Association Series*, pages 10–46.

Davis, D. R. and Weinstein, D. E. (2000). International trade as an" integrated equilibrium": New perspectives. *American Economic Review*, 90(2):150–154.

Davis, D. R., Weinstein, D. E., Bradford, S. C., and Shimpo, K. (1997). Using international and Japanese regional data to determine when the factor abundance theory of trade works. *American Economic Review*, pages 421–446.

Davis, S. J., Grim, C., and Haltiwanger, J. (2008). Productivity dispersion and input prices: The case of electricity. *US Census Bureau Center for Economic Studies Paper No. CES-WP-08-33*.

Davis, S. J., Grim, C., Haltiwanger, J., and Streitwieser, M. (2013). Electricity unit value prices and purchase quantities: US manufacturing plants, 1963–2000. *Review of Economics and Statistics*, 95(4):1150–1165.

Dean, J. M. and Lovely, M. E. (2010). Trade growth, production fragmentation, and China's environment. In *China's growing role in world trade*, pages 429–469. University of Chicago Press.

Dean, J. M., Lovely, M. E., and Wang, H. (2009). Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China. *Journal of Development Economics*, 90(1):1–13.

Dilaver, Z. and Hunt, L. C. (2011). Industrial electricity demand for Turkey: A structural time series analysis. *Energy Economics*, 33(3):426–436.

Dollar, D., Hallward-Driemeier, M., and Mengistae, T. (2005). Investment climate and firm performance in developing economies. *Economic Development and Cultural Change*, 54(1):1–31.

Dreger, C., Wang, T., and Zhang, Y. (2015). Understanding Chinese consumption: The impact of Hukou. *Development and Change*, 46(6):1331–1344.

Dukes, A. J., Gal-Or, E., and Srinivasan, K. (2006). Channel bargaining with retailer asymmetry. *Journal of Marketing Research*, 43(1):84–97.

Dunning, J. H. (1988). The eclectic paradigm of international production: A restatement and some possible extensions. *Journal of International Business Studies*, 19(1):1–31.

Eaton, B. C. and Lipsey, R. G. (1980). Exit barriers are entry barriers: The durability of capital as a barrier to entry. *Bell Journal of Economics*, pages 721–729.

Eberhardt, M. and Teal, F. (2008). Modeling technology and technological change in manufacturing: How do countries differ? *MPRA Paper No. 10690*.

Eckert, A. (2002). Retail price cycles and response asymmetry. *Canadian Journal of Economics*, 35(1):52–77.

Eckert, A. (2003). Retail price cycles and the presence of small firms. *International Journal of Industrial Organization*, 21(2):151–170.

Eckert, A. (2013). Empirical studies of gasoline retailing: A guide to the literature. *Journal of Economic Surveys*, 27(1):140–166.

Eckert, A. and West, D. S. (2004). A tale of two cities: Price uniformity and price volatility in gasoline retailing. *Annals of Regional Science*, 38(1):25–46.

Ecofys, Fraunhofer-ISI, and GWS (2015). Electricity costs of energy intensive industries: An international comparison.

Ederington, J., Levinson, A., and Minier, J. (2005). Footloose and pollution-free. *Review of Economics and Statistics*, 87(1):92–99.

Ederington, J. and Minier, J. (2003). Is environmental policy a secondary trade barrier? An empirical analysis. *Canadian Journal of Economics*, 36(1):137–154.

Egger, H. and Egger, P. (2005). The determinants of eu processing trade. *World Economy*, 28(2):147–168.

Fan, C. S. and Wei, X. (2006). The law of one price: Evidence from the transitional economy of China. *Review of Economics and Statistics*, 88(4):682–697.

Feng, T., Sun, L., and Zhang, Y. (2009). The relationship between energy consumption structure, economic structure and energy intensity in China. *Energy Policy*, 37(12):5475–5483.

Financial Times (2015). China oil imports surpass those of US.

Fisher-Vanden, K., Jefferson, G. H., Liu, H., and Tao, Q. (2004). What is driving China's decline in energy intensity? *Resource and Energy Economics*, 26(1):77–97.

Fisher-Vanden, K., Mansur, E. T., and Wang, Q. J. (2015). Electricity shortages and firm productivity: Evidence from China's industrial firms. *Journal of Development Economics*, 114:172–188.

Fredrich Kahrl, Jim Williams, D. J. (2011). Four things you should know about China's electricity system.

Fuss, M. A. (1977). The demand for energy in Canadian manufacturing: An example of the estimation of production structures with many inputs. *Journal of Econometrics*, 5(1):89–116.

Galli, R. (1998). The relationship between energy intensity and income levels: forecasting long term energy demand in Asian emerging countries. *The Energy Journal*, pages 85–105.

Gan, L. (2014). Urbanization and the housing market in china. *China Household Finance Survey*.

Ganapati, S., Shapiro, J. S., and Walker, R. (2016). The incidence of carbon taxes in US manufacturing: Lessons from energy cost pass-through. *National Bureau of Economic Research No. w22281*.

Garbaccio, R. F., Ho, M. S., Jorgenson, D. W., and John, F. (1999). Why has the energy-output ratio fallen in China? *The Energy Journal*, 20(3):63–91.

Gerardi, K. S. and Shapiro, A. H. (2009). Does competition reduce price dispersion? New evidence from the airline industry. *Journal of Political Economy*, 117(1):1–37.

Gerlagh, R. and Mathys, N. A. (2011). Energy abundance, trade and industry location. *FEEM working paper No. 3.2011*.

Gerlagh, R., Mathys, N. A., and Michielsen, T. O. (2015). Energy abundance, trade and specialization. *Energy Journal*, 36(3).

Geroski, P. A., Mata, J., and Portugal, P. (2010). Founding conditions and the survival of new firms. *Strategic Management Journal*, 31(5):510–529.

Gielens, K., Van de Gucht, L. M., Steenkamp, J.-B. E., and Dekimpe, M. G. (2008). Dancing with a giant: The effect of Wal-Mart's entry into the United Kingdom on the performance of European retailers. *Journal of Marketing Research*, 45(5):519–534.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010). Multiproduct firms and product turnover in the developing world: Evidence from India. *Review of Economics and Statistics*, 92(4):1042–1049.

Grether, J.-M., Hotz, I., and Mathys, N. A. (2014). Industry location in Chinese provinces: Does energy abundance matter? *Energy Economics*, 44:383–391.

Griffith, R., Redding, S., and Van Reenen, J. (2004). Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. *Review of Economics and Statistics*, 86(4):883–895.

Griliches, Z. and Mairesse, J. (1991). Comparing productivity growth: An exploration of French and US industrial and firm data. In *International Volatility and Economic Growth: The First Ten Years of The International Seminar on Macroeconomics*, pages 45–82. Elsevier Science Publishers BV.

Groves, T., Hong, Y., McMillan, J., and Naughton, B. (1994). Autonomy and incentives in Chinese state enterprises. *Quarterly Journal of Economics*, pages 183–209.

GTAP (2006). HS2002-CPC 1.1-ISIC, Rev3-GTAP Concordance. *Global Trade Analysis Project: Purdue University*.

Hakura, D. S. (2001). Why does HOV fail?: The role of technological differences within the EC. *Journal of International Economics*, 54(2):361–382.

Hall, B. H. (1986). The relationship between firm size and firm growth in the US manufacturing sector. *NBER Working Paper No.1965*.

Hallward-Driemeier, M. and Stewart, D. (2004). How do investment climate conditions vary across countries, regions and types of firms? *World Development Report*.

Hang, L. and Tu, M. (2007). The impacts of energy prices on energy intensity: Evidence from China. *Energy Policy*, 35(5):2978–2988.

Hanna, R. (2010). US environmental regulation and FDI: Evidence from a panel of US-based multinational firms. *American Economic Journal: Applied Economics*, 2(3):158–189.

Hastings, J. S. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in Southern California. *American Economic Review*, 94(1):317–328.

Hastings, J. S. and Gilbert, R. J. (2005). Market power, vertical integration and the wholesale price of gasoline. *Journal of Industrial Economics*, 53(4):469–492.

Hausman, J. and Leibtag, E. (2007). Consumer benefits from increased competition in shopping outlets: Measuring the effect of Wal-Mart. *Journal of Applied Econometrics*, 22(7):1157–1177.

Heck, T. and Hirschberg, S. (2011). China: Economic impacts of air pollution in the country. *Encyclopedia of Environmental Health*, 1:625–640.

Herrerias, M. J., Cuadros, A., and Orts, V. (2013). Energy intensity and investment ownership across Chinese provinces. *Energy Economics*, 36:286–298.

Hoechle, D. et al. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, 7(3):281.

Holmes, M. J., Otero, J., and Panagiotidis, T. (2011). Investigating regional house price convergence in the United States: Evidence from a pair-wise approach. *Economic Modelling*, 28(6):2369–2376.

Holmes, M. J., Otero, J., and Panagiotidis, T. (2013). On the dynamics of gasoline market integration in the United States: Evidence from a pair-wise approach. *Energy Economics*, 36:503–510.

Horrace, W. C. and Oaxaca, R. L. (2006). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics Letters*, 90(3):321–327.

Hou, Q., An, X., Wang, Y., Tao, Y., and Sun, Z. (2012). An assessment of China's PM 10-related health economic losses in 2009. *Science of the Total Environment*, 435:61–65.

Hu, A. G., Jefferson, G. H., and Jinchang, Q. (2005). R&D and technology transfer: Firm-level evidence from Chinese industry. *Review of Economics and Statistics*, 87(4):780–786.

Huang, K. (2015). New faces, new reforms for Big Oil in China. *Caixin Global*, May 14.

Hunt, L. C. (1984). Energy and capital: Substitutes or complements? Some results for the UK industrial sector. *Applied Economics*, 16(5):783–789.

IEA and OECD (2006). China's power sector reforms.

Jefferson, G. H. and Rawski, T. G. (1994). Enterprise reform in Chinese industry. *Journal of Economic Perspectives*, 8(2):47–70.

Jiang, L., Folmer, H., and Ji, M. (2014). The drivers of energy intensity in China: A spatial panel data approach. *China Economic Review*, 31:351–360.

Jiang, Z. and Lin, B. (2012). China's energy demand and its characteristics in the industrialization and urbanization process. *Energy Policy*, 49:608–615.

Jones, D. (2004). Urbanization and energy. *Encyclopedia of Energy*, 6(January):329–335.

Jones, D. W. (1989). Urbanization and energy use in economic development. *The Energy Journal*, 10(4):29–44.

Jones, D. W. (1991). How urbanization affects energy-use in developing countries. *Energy Policy*, 19:621–630.

Khanna, N. Z., Zhou, N., Fridley, D., and Fino-Chen, C. (2013). Evaluation of China's local enforcement of energy efficiency standards and labeling programs for appliances and equipment. *Energy Policy*, 63:646–655.

Khayyat, N. T. (2015). *Literature on Energy Demand*. Springer.

Kim, S. (1999). Regions, resources, and economic geography: Sources of US regional comparative advantage, 1880–1987. *Regional Science and Urban Economics*, 29(1):1–32.

Klein, A. and Crafts, N. (2012). Making sense of the manufacturing belt: Determinants of US industrial location, 1880–1920. *Journal of Economic Geography*, 12(4):775–807.

Klepper, S. (1996). Entry, exit, growth, and innovation over the product life cycle. *American Economic Review*, pages 562–583.

Krey, V., O'Neill, B. C., van Ruijven, B., Chaturvedi, V., Daioglou, V., Eom, J., Jiang, L., Nagai, Y., Pachauri, S., and Ren, X. (2012). Urban and rural energy use and carbon dioxide emissions in Asia. *Energy Economics*, 34(SUPPL. 3):S272–S283.

Lan, J., Kakinaka, M., and Huang, X. (2012). Foreign direct investment, human capital and environmental pollution in China. *Environmental and Resource Economics*, 51(2):255–275.

Leontief, W. (1953). Domestic production and foreign trade: The American capital position re-examined. *Proceedings of the American Philosophical Society*, 97(4):332–349.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, 70(2):317–341.

Levinson, A. and Taylor, M. S. (2008). Unmasking the pollution haven effect. *International Economic Review*, 49(1):223–254.

Lewis, M. and Noel, M. (2011). The speed of gasoline price response in markets with and without Edgeworth cycles. *Review of Economics and Statistics*, 93(2):672–682.

Lewis, M. S. (2009). Temporary wholesale gasoline price spikes have long-lasting retail effects: The aftermath of Hurricane Rita. *Journal of Law and Economics*, 52(3):581–605.

Li, X., Liu, X., and Parker, D. (2001). Foreign direct investment and productivity spillovers in the Chinese manufacturing sector. *Economic Systems*, 25(4):305–321.

Liao, H., Fan, Y., and Wei, Y. M. (2007). What induced China's energy intensity to fluctuate: 1997-2006? *Energy Policy*, 35(9):4640–4649.

Liddle, B. (2003). Demographic dynamics and per capita environmental impact: Using panel regressions and household decompositions to examine population and transport. *MPIDR Working Papers*, 26(1):23–39.

Liu, H. (2007). A study of China's energy consumption and economic growth relationship-a case of petroleum. *Journal of Noah China Electric Power University (Social Science Edition)*, 4:17–22.

Liu, J. (2004). The difference between registration population and permanent population (in chinese). *Beijing Statistics*, 1:6–7.

Liu, X. and Liang, W. (1997). Zhejiangcun: Social and spatial implications of informal urbanization on the periphery of Beijing. *Cities*, 14(2):95–108.

Liu, Y. (2009). Exploring the relationship between urbanization and energy consumption in China using ARDL (autoregressive distributed lag) and FDM (factor decomposition model). *Energy*, 34(11):1846–1854.

Lo, K. (2014). A critical review of China's rapidly developing renewable energy and energy efficiency policies. *Renewable and Sustainable Energy Reviews*, 29:508–516.

Long, X., Ji, X., and Ulgiati, S. (2016). Is urbanization eco-friendly? An energy and land use cross-country analysis. *Energy Policy*, 2006.

Lu, S. (2010). Understanding China's retail market. *China Business Review*, 36(3):16–19.

Ma, B. (2015). Does urbanization affect energy intensities across provinces in China? Long-run elasticities estimation using dynamic panels with heterogeneous slopes. *Energy Economics*, 49:390–401.

Ma, C. and Stern, D. I. (2008). China's changing energy intensity trend: A decomposition analysis. *Energy Economics*, 30(3):1037–1053.

Ma, H. and Oxley, L. (2012). The emergence and evolution of regional convergence clusters in China's energy markets. *Energy Economics*, 34(1):82–94.

Ma, H., Oxley, L., and Gibson, J. (2009). Gradual reforms and the emergence of energy market in China: Evidence from tests for convergence of energy prices. *Energy Policy*, 37(11):4834–4850.

Maddison, D. (2006). Environmental Kuznets curves: A spatial econometric approach. *Journal of Environmental Economics and Management*, 51(2):218–230.

Madlener, R. and Sunak, Y. (2011). Impacts of urbanization on urban structures and energy demand: What can we learn for urban energy planning and urbanization management? *Sustainable Cities and Society*, 1(1):45–53.

Magnus, J. R. (1979). Substitution between energy and non-energy inputs in the Netherlands 1950-1976. *International Economic Review*, pages 465–484.

Malenbaum, W. (1978). *World demand for raw materials in 1985 and 2000*. McGraw-Hill E/Mj Mining Informational Services.

Martínez-Zarzoso, I. and Maruotti, A. (2011). The impact of urbanization on CO2 emissions: Evidence from developing countries. *Ecological Economics*, 70(7):1344–1353.

Maskin, E. and Tirole, J. (1988). A theory of dynamic oligopoly, II: Price competition, kinked demand curves, and Edgeworth cycles. *Econometrica: Journal of the Econometric Society*, pages 571–599.

Mata, J. and Portugal, P. (2002). The survival of new domestic and foreign-owned firms. *Strategic Management Journal*, 23(4):323–343.

Mazzanti, M. and Zoboli, R. (2009). Environmental efficiency and labour productivity: Trade-off or joint dynamics? A theoretical investigation and empirical evidence from Italy using NAMEA. *Ecological Economics*, 68(4):1182–1194.

Michielsen, T. O. (2013). The distribution of energy-intensive sectors in the USA. *Journal of Economic Geography*, 13(5):871–888.

Midelfart, K. H., Overman, H. G., and Venables, A. J. (2000). Comparative advantage and economic geography: Estimating the location of production in the EU. *Norwegian School of Economics and Business Administration Discussion Paper*.

Minniti, A. (2006). Multi-product firms, R&D, and growth. *Topics in Macroeconomics*, 6(3).

Minx, J. C., Baiocchi, G., Peters, G. P., Weber, C. L., Guan, D., and Hubacek, K. (2011). A "Carbonizing Dragon": China's fast growing CO 2 emissions revisited. *Environmental Science & Technology*, pages 9144–9153.

Mishra, V., Smyth, R., and Sharma, S. (2009). The energy-GDP nexus: Evidence from a panel of Pacific Island countries. *Resource and Energy Economics*, 31(3):210–220.

Mitchell, W., Shaver, J. M., and Yeung, B. (1994). Foreign entrant survival and foreign market share: Canadian companies' experience in United States medical sector markets. *Strategic Management Journal*, 15(7):555–567.

Mulatu, A., Gerlagh, R., Rigby, D., and Wossink, A. (2010). Environmental regulation and industry location in Europe. *Environmental and Resource Economics*, 45(4):459–479.

Mulder, P., de Groot, H. L. F., and Pfeiffer, B. (2014). Dynamics and determinants of energy intensity in the service sector: A cross-country analysis, 1980-2005. *Ecological Economics*, 100:1–15.

NBSC (2015). National Migrant Workers Monitoring Survey Report 2014.

NBSC (2016). http://data.stats.gov.cn/.

Newman, C., Rand, J., and Tarp, F. (2013). Industry switching in developing countries. *World Bank Economic Review*, 27(2):357–388.

Ngan, H. (2010). Electricity regulation and electricity market reforms in China. *Energy Policy*, 38(5):2142–2148.

Noel, M. (2009). Do retail gasoline prices respond asymmetrically to cost shocks? The influence of Edgeworth Cycles. *RAND Journal of Economics*, 40(3):582–595.

Noel, M. D. (2007a). Edgeworth price cycles, cost-based pricing, and sticky pricing in retail gasoline markets. *Review of Economics and Statistics*, 89(2):324–334.

Noel, M. D. (2007b). Edgeworth price cycles: Evidence from the Toronto retail gasoline market. *Journal of Industrial Economics*, 55(1):69–92.

Noel, M. D. (2011). Edgeworth price cycles. *New Palgrave Dictionary of Economics. Palgrave Macmillan*.

Norman, J., MacLean, H., and Kennedy, C. (2006). Comparing high and low residential density: Life-cycle analysis of energy use and greenhouse gas emissions. *Journal of Urban Planning and Development*, 132(1):10–21.

O'Neill, B. C., Ren, X., Jiang, L., and Dalton, M. (2012). The effect of urbanization on energy use in India and China in the iPETS model. *Energy Economics*, 34(SUPPL. 3):S339–S345.

Pablo-Romero, M. d. P. and Sánchez-Braza, A. (2015). Productive energy use and economic growth: Energy, physical and human capital relationships. *Energy Economics*, 49:420–429.

Parikh, J. and Shukla, V. (1995). Urbanization , energy use and greenhouse effects in economic development study of developing countries. *Global Environmental Change*, 5.

Patterson, M. G. (1996). What is energy efficiency?: Concepts, indicators and methodological issues. *Energy Policy*, 24(5):377–390.

People's Daily (2014). Oil production rises 0.7% while import dependence hits 60% in 2014.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *SSRN Electronic Journal*, 1229(August).

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with cross section dependence. *Econometrica*, 74(4):967–1012.

Pesaran, M. H. (2007a). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22:265–312.

Pesaran, M. H. (2007b). A pair-wise approach to testing for output and growth convergence. *Journal of Econometrics*, 138(1):312–355.

Pesaran, M. H. and Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1):79–113.

Pesaran, M. H., Smith, R. P., Yamagata, T., and Hvozdyk, L. (2009). Pairwise tests of purchasing power parity. *Econometric Reviews*, 28(6):495–521.

Poumanyvong, P. and Kaneko, S. (2010). Does urbanization lead to less energy use and lower CO2 emissions? A cross-country analysis. *Ecological Economics*, 70(2):434–444.

Qin, B. and Zhang, Y. (2014). Note on urbanization in China: Urban definitions and census data. *China Economic Review*, 30:495–502.

Rafiq, S., Salim, R., and Nielsen, I. (2016). Urbanization, openness, emissions, and energy intensity: A study of increasingly urbanized emerging economies. *Energy Economics*, 56:20–28.

Ramzy, A. (2014). Beijing's neighbors resist transfer of its polluting industries. *The New York Times*.

Redding, S. J., Bernard, A. B., and Schott, P. K. (2006). Multi-product firms and product switching. *CEPR Discussion Paper No. 5708*.

Ricardo, D. (1817). *Principles of political economy and taxation*. London: John Murray.

Rogers, W. (1994). Regression standard errors in clustered samples. *Stata Technical Bulletin*, 3(13).

Romalis, J. (2004). Factor proportions and the structure of commodity trade. *American Economic Review*, pages 67–97.

Ru, X., Lu, X., and Li, P. (2012). Blue book of China's society 2012: Society of China analysis and forecast (2012). *Social Science Academic Press*.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, 2(3):169–188.

Sadorsky, P. (2013). Do urbanization and industrialization affect energy intensity in developing countries? *Energy Economics*, 37:52–59.

Sato, M. and Dechezleprêtre, A. (2015). Asymmetric industrial energy prices and international trade. *Energy Economics*, 52:S130–S141.

Schneider, F. and Enste, D. (2000). Shadow economies around the world size, causes, and consequences. *Journal of Economic Literature*, 38(1):77–114.

SDRC (2016). http://jgjc.ndrc.gov.cn/.

Shao, Y. and Jia, M. J. (2006). China's economic sustainable development and energy consumption. *Journal of Xian Petroleum University (social science edition)*, pages 5–9.

Shaver, J. M., Mitchell, W., and Yeung, B. (1997). The effect of own-firm and other-firm experience on foreign direct investment survival in the United States, 1987-92. *Strategic Management Journal*, pages 811–824.

Shen, J. (2002). A study of the temporary population in Chinese cities. *Habitat International*, 26(3):363–377.

Song, F. and Zheng, X. (2012). What drives the change in China's energy intensity: Combining decomposition analysis and econometric analysis at the provincial level. *Energy Policy*, 51:445–453.

Tan, X. and Wolak, F. (2009). Does China underprice its oil consumption? *Department of Economics, Stanford University*.

The Economist (2014). Moving on up. *The Economist, 22 March 2014*.

The Economist (2015). Mapping the invisible scourge. *The Economist, 15 August 2015*.

UNEP (2012). Cities and Buildings UNEP initiatives and projects.

United Nations (1997). Glossary of environment statistics, studies in methods. *New York*.

United Nations (2014). World urbanization prospects.

US ITC (2007). *China: Description of Selected Government Practices and Policies Affecting Decision Making in the Economy, Inv. 332-492*. DIANE Publishing.

Utterback, J. M. and Abernathy, W. J. (1975). A dynamic model of process and product innovation. *Omega*, 3(6):639–656.

Vita, M. G. (2000). Regulatory restrictions on vertical integration and control: The competitive impact of gasoline divorcement policies. *Journal of Regulatory Economics*, 18(3):217–233.

Wang, Q. (2014). Effects of urbanisation on energy consumption in China. *Energy Policy*, 65:332–339.

Wang, Q., Qiu, H.-N., and Kuang, Y. (2009). Market-driven energy pricing necessary to ensure China's power supply. *Energy Policy*, 37(7):2498–2504.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

World Bank (2014). Electricity production from coal sources.

Wu, H., Guo, H., Zhang, B., and Bu, M. (2017). Westward movement of new polluting firms in China: Pollution reduction mandates and location choice. *Journal of Comparative Economics*, 45(1):119–138.

Yan, H. (2015). Provincial energy intensity in China: The role of urbanization. *Energy Policy*, 86:635–650.

Yang, R. and He, C. (2014). The productivity puzzle of Chinese exporters: Perspectives of local protection and spillover effects. *Papers in Regional Science*, 93(2):367–384.

Yazgan, M. E. and Yilmazkuday, H. (2011). Price-level convergence: New evidence from US cities. *Economics Letters*, 110(2):76–78.

Yilmazkuday, D. and Yilmazkuday, H. (2016). Understanding gasoline price dispersion. *Annals of Regional Science*, 57(1):223–252.

York, R. (2007). Demographic trends and energy consumption in European Union Nations, 1960-2025. *Social Science Research*, 36(3):855–872.

Zeng, D.-Z. and Zhao, L. (2009). Pollution havens and industrial agglomeration. *Journal of Environmental Economics and Management*, 58(2):141–153.

Zhang, C. and Lin, Y. (2012). Panel estimation for urbanization, energy consumption and CO 2 emissions: A regional analysis in China. *Energy Policy*, 49:488–498.

Zhang, K. H. and Song, S. (2003). Rural-urban migration and urbanization in China: Evidence from time-series and cross-section analyses. *China Economic Review*, 14(4):386–400.

Zhang, M., Song, Y., Cai, X., and Zhou, J. (2008). Economic assessment of the health effects related to particulate matter pollution in 111 Chinese cities by using economic burden of disease analysis. *Journal of Environmental Management*, 88(4):947–954.

Zhang, Y. and Huang, Z. (2010). Re-evaluation on the level and pace of China's urbanization. *Urban Studie*, 11(003).

Zhang, Z. (2011). *Energy and Environmental Policy in China: Towards a Low-Carbon Economy*. Edward Elgar Publishing.

Zhao, J. and Fan, J. (2008). Empirical research on the inherent relationship between economy growth and energy consumption in China. *Economic Research Journal*, 8:31–42.

Zhou, N., Levine, M. D., and Price, L. (2010). Overview of current energy-efficiency policies in China. *Energy Policy*, 38(11):6439–6452.

Zhu, H. M., You, W. H., and fa Zeng, Z. (2012). Urbanization and CO2 emissions: A semi-parametric panel data analysis. *Economics Letters*, 117(3):848–850.

Zhu, Y. (1998). Formal and informal urbanisation in China. *Third World Planning Review*, 20(3):267–284.

Zimmerman, P. R. (2012). The competitive impact of hypermarket retailers on gasoline prices. *Journal of Law and Economics*, 55(1):27–41.