Household Finance, Consumption and Health: Evidence from China and European Countries

by

DANYING LI

A thesis submitted to the University of Birmingham for the degree of

DOCTOR OF PHILOSOPHY

Department of Economics

Birmingham Business School

College of Social Sciences

University of Birmingham

September 2018

Abstract

This thesis presents three empirical studies on household finance. The first study investigates the determinants of household financial inclusion and its impact on household consumption in China. The second study looks at the extent to which households' consumption profile changes after health shocks in China. The third study estimates the association between financial stress and body weight status in nine European countries. All studies are based on micro-level survey data. This thesis is inspired by the following phenomena: (1) the development of household finance as an emerging and thriving field in literature; (2) the importance of enhancing financial inclusion in both developing and developed countries; (3) the rising prevalence of obesity in western countries; (4) the global ageing challenge.

Using the 2013 wave of the China Household Finance Survey, I investigate the determinants of financial inclusion in China, focusing on the role played by informal finance. I then test the extent to which financial inclusion affects households' consumption. I find that informal financing is positively related to the probability of having formal loans, but negatively related to the probability of owning bank accounts and credit cards. After controlling for the potential endogeneity of informal finance, only the latter association remains significant. Next, I find that financial inclusion is associated with a higher level of household consumption. These findings suggest that enhancing financial inclusion in China may play an important role in rebalancing the economy towards domestic consumption.

Using the 2011, 2013 and 2015 waves of the China Health and Retirement Longitudinal Study, I investigate the extent to which households' consumption profile changes after health shocks. I find that health shocks are significantly associated with increases in out-of-pocket medical expenditure, but not with changes in other non-medical expenditures. The increase in out-of-pocket medical expenditure after health shocks is higher for urban and poorer residents, as well as for individuals living in provinces with a better healthcare system. These findings suggest that non-medical consumption is generally insured against health shocks in China.

Using the Survey of Health, Ageing and Retirement in Europe over the period 2004-2015, and controlling for the state dependence of body weight as well as individual heterogeneity, I find a positive association between financial stress and body weight in Austria, Germany, Sweden, Spain, Italy, France and Switzerland. This association is robust to controlling for measurement error in self-reported weight in Austria, Germany and Spain, and to using an objective measure of financial stress in Germany and Spain only. These findings suggest that the association between financial status and body weight is weak. I also find that individuals are more likely to respond to self-perceived financial stress than to objective levels of debt. Thus, policies aimed at improving citizens' ability to cope with financial stress and at reducing self-perceived financial stress may play a role in tackling the obesity epidemic in EU countries such as Germany and Spain.

Declaration

I hereby declare that this thesis is my own original work except where stated otherwise by reference in the text. It has not been submitted, in whole or in part, for any other degree or qualification at this or any other university. Further, I have acknowledged and correctly referenced the work of others.

This thesis is dedicated to

my partner and best friend Oliver Hölzinger

for his unconditional love, support, and encouragement.

Without him,

this thesis would not have been possible.

Ich liebe dich, mein Schatz.

Acknowledgements

I would like to express my greatest gratitude to my primary supervisor Professor Alessandra Guariglia for her valuable guidance and support throughout the writing of this thesis. Her professional research standards have led my way in this journey. She is an excellent scholar with cutting-edge ideas and insights, who has inspired and nourished my research. Her dedication and persistence into research have motivated me to continue my future in academia. She has been, and I know she will always be my mentor whom I trust, admire, and learn from.

Furthermore, I would like to thank my supervisor Mr Nicholas Horsewood for his help, advice, and insightful comments on my work. I always benefit greatly from meetings with him. I also appreciate the financial support he has given me. Without this, my visit at the Southwestern University of Finance and Economics (SWUFE) and attendance at some conferences would not have been possible.

I am also grateful to Professor David Dickinson and the China Research Cluster at the University of Birmingham for offering me research funding to attend conferences and workshops. In addition, I would like to thank Professor Anindya Banerjee and the Department of Economics for the scholarship that supported me to finish this thesis. I feel indebted to Professor Dayong Zhang for providing me with a valuable opportunity to use the China Household Finance Survey Database on site and for his useful comments on my work in general. I appreciate his support and help throughout my visit at SWUFE.

I would like to thank my seniors Dr Rong Huang, Dr Yanan Zhang, Dr Junhong Yang and Dr Marco Giansoldati for sharing their valuable experience with me and for encouraging me whenever I was in self-doubt. I truly appreciate my lovely colleagues Fei Wu, Yaopeng Wang, Lin Fu, Wei Jin and others in our Panda Team sharing my life moments and providing comments on my work throughout my PhD study.

At last, my deepest gratitude goes to my father Ruiqin Li, who has been supporting me to his best since the first day I was born.

Danying Li (Tara)

September 2018

Table of Contents

List of Abbreviations

Add Health	National Longitudinal Study of Adolescent Health
ADL	Activity of Daily Living
ATT	Average Treatment Effect on the Treated
BHPS	British Household Panel Survey
BMI	Body Mass Index
CDC	Centres for Disease Control and Prevention
CEO	Chief Executive Officer
CES-D	Centre for Epidemiologic Studies Depression Scale
CHARLS	China Health and Retirement Longitudinal Study
CHFS	China Household Finance Survey
CHNS	China Household Nutrition Survey
CPI	Consumer Price Index
ECPH	European Community Household Panel
ELSA	English Longitudinal Study of Ageing
EU	European Union
EU-SILC	European Statistics on Income and Living Conditions
FA	Factor Analysis
FI	Financial Inclusion
GDP	Gross Domestic Product
GNI	Gross National Income
HAQ	Healthcare Access and Quality
HILDA	Household, Income and Labour Dynamics in Australia
HRS	Health and Retirement Study
IMF	International Monetary Fund
IV	Instrumental Variable
LCH	Life-Cycle Hypothesis
LMIC	Low- and Middle-Income Country
LPM	Linear Probability Model

MA	Medical Aid
NBS	National Bureau of Statistics
NHANES I/II/III	The First/Second/Third National Health and Nutrition Examination Study
NLSY97	National Longitudinal Survey of Youth, the 1997 Cohort
NRCMS	New Rural Co-operative Medical Scheme
ODC	Other Depository Corporation
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Square
OOP	Out-of-pocket
PIH	Permanent Income Hypothesis
PRC	People’s Republic of China
PSM	Propensity Score Matching
QR	Quantile Regression
RE	Random-effects
RMB	Renminbi
SCF	Survey of Consumer Finance
SES	Socioeconomic Status
SHARE	Study of Health and Retirement in Europe
SR	Special Regressor
TFP	Total Factor Productivity
UEBMI	Urban Employee Basic Medical Insurance
UK	United Kingdom
UKHLS	UK Household Longitudinal Study
UN	United Nations
URBMI	Urban Resident Basic Medical Insurance
US	United States
USD	United States Dollar
WHO	World Health Organisation

List of Figures

Chapter Two

Chapter Three

List of Tables

Chapter Two

Chapter Three

Chapter Four

Chapter One: Introduction

As an emerging and thriving field, household finance has gradually gained its own title and identity in the past decade (Guiso and Sodini, 2013). This thesis presents three empirical studies on household finance. Specifically, the first study investigates the determinants of household financial inclusion and its impact on household consumption in China. The second study looks at the extent to which households' consumption profile changes after health shocks in China. The third study estimates the association between financial stress and body weight status in nine European countries. All studies use micro-level survey data.

This thesis is inspired by the following phenomena[1]. Firstly, due to the global development of the financial sector, households and individuals interact with finance in multiple ways: financial services provide them with a range of ways to make and receive transfers and payments, to make inter-temporal saving and dissaving arrangements, to obtain credit when facing liquidity shortage, and to be insured when facing uncertainty. Financial inclusion, defined as the use of formal financial services, is recognised as an important contributor to global economic growth (Allen et al., 2012, Demirgüç-Kunt and Klapper, 2013). Both developing and developed countries are committed to improve financial inclusion. However, the development of financial inclusion is uneven across countries. There exist greater accessibility and availability of financial services in developed countries than in developing ones. In the developing world, countries like China are endeavouring to stimulate the use of financial services including bank loans, whilst in developed countries, household indebtedness is gradually becoming a concern for policy makers.

[1] The background of this thesis is only briefly mentioned in this chapter. A more detailed presentation of this background can be found in each subsequent chapter. This is to avoid being largely repetitive.

Secondly, population ageing, as the consequence of increasing longevity as well as decreasing fertility and mortality rates, is becoming a global challenge. A United Nation report (United Nations, 2002) has identified this challenge as *unprecedented*, *pervasive*, *enduring* and *influential*. Ageing and health, have attracted great attentions from policy makers and academics alike. With the increasing size and percentage of the older population, understanding older people's behaviour and needs, in order to provide them with sufficient support and care, has never been so important around the world. However, to ensure healthy ageing, the challenges that need to be addressed differ between developing and developed countries. In developing countries like China, providing health security at affordable prices is the key to facilitate healthy ageing because the proportion of out-of-pocket health expenditure relative to the total health expenditure is still very high compared to that of developed countries. In developed countries, the prevalence of obesity has posed a serious threat to healthy ageing.

In this context, I firstly look at the determinants of financial inclusion and its impact on consumption in China. This is important considering that developing financial inclusion is one of the main national strategies of the Chinese government[2]. Secondly, in the context of the high proportion of out-of-pocket medical expenditure that Chinese residents need to pay, I investigate the extent to which Chinese households' consumption is insured against one of the most common uncertainties in older age, namely health shocks. Thirdly, considering that the prevalence of indebtedness and obesity has been rising rapidly over the past decades in Europe, I test the extent to which financial stress, a consequence of the extensive use of financial services, is associated with being obese and/or overweight in nine European Union (EU)

[2] The National Plan of Promoting Financial Inclusion can be found: http://www.gov.cn/zhengce/content/2016-01/15/content_10602.htm

counties. The findings presented in this thesis will provide empirical evidence for the merits of developing household finance and insights on healthy ageing.

The remainder of this thesis is organised as follows. Section 1.1 of this chapter presents the outline of each study. The contributions of this thesis are discussed in Section 1.2. Three empirical studies are presented in Chapter Two, Chapter Three and Chapter Four, respectively. Chapter Five concludes the thesis.

1.1. Thesis outline

In Chapter Two, I empirically investigate the determinants of financial inclusion in China. I further test the extent to which financial inclusion is associated with a higher level of household consumption. Financial inclusion in this study is defined in four ways: having a bank account, having a credit card or using a credit card when purchasing goods, having a bank loan, and using either one of the three above-mentioned financial services. It is worth mentioning that I exclude those who express having no need of using these financial services from all analyses due to the clear distinctions between voluntary and involuntary financial exclusions. From the policy makers' perspective, voluntary exclusions are not problematic because they are driven by lack of demand rather than lack of access (Demirgüç-Kunt et al., 2008).

In developing countries like China, informal finance which is defined as credit from family members and/or friends, is especially prevalent compared to developed countries, where bank credit is the main borrowing source (Demirgüç-Kunt et al., 2008). I thus investigate whether informal finance affects households' ability to obtaining formal financial services. Using the 2013 wave of the China Household Finance Survey which contains detailed information on 28,100 Chinese households' income, assets, debts, as well as their social and demographic characteristics, I estimate a set of probit specifications with each financial inclusion indicator, in turn, acting as the dependent variable. Conditioning on households' characteristics such as the household head's age, gender, education level, job and marital status, financial literacy and risk attitude, as well as household income, net wealth, household size, home ownership and residential region, I find that informal finance is a substitute to formal financial services such as bank accounts, credit cards, as well as bank loans. Other positive determinants of financial inclusion include having a younger household head, having a higher education level, being married, having higher income and net wealth, being a Communist Party member, being less risk averse and having better financial literacy. These findings are robust to instrumenting the potentially endogenous variable possession of informal loans using whether or not the household head and his/her spouse have siblings as an instrument. Furthermore, based on results from a set of ordinary least square (OLS) estimations, I find that financial inclusion indicators are associated with a higher household consumption. This finding confirms that developing financial inclusion may be a valid tool for boosting domestic consumption in China, which is one of the priorities established by the Chinese government.

In Chapter Three, I investigate the extent to which Chinese households' consumption is affected by health shocks. Although China has achieved a universal coverage of public health insurance schemes in 2011, there has been a debate over the efficiency of these schemes. The schemes significantly reduce household out-of-pocket medical expenditure, but the reduction is uneven across regions and between groups with higher and lower income/wealth (Zhang et al., 2017). In this context, the second study investigates the extent to which households' consumption profile changes after health shocks using data taken from the China Health and Retirement Longitudinal Study covering year 2011 to 2015. I focus on individuals aged 45 and over because population ageing is recognised as a great challenge in China and older individuals are more prone to health risks than the younger cohorts. Following the literature, I define health shocks as the onset of severe medical conditions, the onset of moderate medical conditions, as well as a large deterioration of mobility. Based on a set of random-effects estimations as well as propensity score matching techniques, I find that health shocks are associated with an 8.1 to 19.1 percent increase in out-of-pocket medical expenditure. The magnitude of this association depends on the health shock indicator and model specification. In addition, the increase in out-of-pocket expenditure is higher for urban residents, poor respondents, as well as residents living in provinces with a better healthcare system. In addition, I find that households' expenditure on non-medical items remains unchanged following health shocks, for all groups. This suggests that Chinese households' non-medical consumption is insured against health shocks.

In Chapter Four, I empirically test the extent to which financial stress is associated with a higher likelihood of being obese/overweight in nine EU countries[3], taking into account the state dependence of body weight as well as individual heterogeneity. Again, I focus on older individuals because of the global population ageing concern. By applying a dynamic analysis framework to data from waves one to six of the Survey of Health, Aging, and Retirement in Europe (covering the period 2004 - 2015), I find that the association between financial stress and being obese/overweight only exists in some countries and this association is small in magnitude. I also find that the association is higher and more significant when financial stress is measured subjectively than objectively. This finding indicates that individuals' self-perception of bearing debts is more likely to affect their body weight compared to the actual amount of debts they bear. This finding also suggests that providing financially stressed individuals with financial management training aimed at increasing their self-perceived capability and confidence of dealing with financial hardships may have impact on reducing obesity/overweight in European countries such as Germany and Spain.

[3] They are Austria, Germany, Sweden, Spain, Italy, France, Denmark, Switzerland and Belgium. Sample selection criteria are discussed in Section 4.3, Chapter Four.

1.2. Contributions to the literature

This thesis makes the following contributions to the existing literature. In Chapter Two, I test for the first time in literature the intertwined relationship between formal and informal finance, at the household level in China. Most studies on this topic, such as Allen et al. (2018), Guariglia et al. (2011) and Zhang (2008), have investigated the relationship between formal and informal finance at the firm-level. Cull et al. (2015a) has studied the dual existence of formal and informal finance at the household level in China, but the association between them is not discussed in their paper. In addition, for the first time, the *voluntary exclusion* issue, whereby individuals voluntarily choose to be excluded from financial services because they do not need them, is taken into account. Given the extensive use of informal finance in China, understanding the relationship between formal and informal finance helps promote financial inclusion and achieve the goal of boosting domestic consumption.

In Chapter Three, I investigate the extent to which both objectively and subjectively measured health shocks affect Chinese older people's consumption. In the literature, only a few studies on this topic have focused on older people in China and none of them has measured health shocks in multiple ways. In addition, the dataset used in this study is very recent. Since the universal coverage of public health insurance was just achieved recently, there lacks research on analysing households' consumption profile following health shocks after public health insurance was made universally available in China. Thus, a timely investigation on this topic is of great importance. My findings will provide insights on addressing the healthy ageing issue in China.

In Chapter Four, I conduct a comparative study across nine EU countries on the extent to which financial stress is associated with higher body weight. To the best of my knowledge, none of the existing studies analyse the finance-health nexus in a country-specific comparison setting. Additionally, the majority of existing studies on the finance-health link focus on mental health outcomes. This chapter thus contributes to the literature by estimating the association between financial stress and body weight. Furthermore, among studies looking at the finance-weight link, this study is the first to take into account the persistence of body weight, as well as initial conditions. In the context of increasing prevalence of obesity/overweight and household indebtedness in Europe, this work sheds new light on understanding the epidemic of obesity in European countries.

Chapter Two: Financial Inclusion, Informal Finance, and Consumption: An Empirical Investigation on Chinese

2.1. Introduction

Financial inclusion, generally defined as the use of financial services, has been considered as an important determinant of global economic growth (Allen et al., 2012, Demirgüç-Kunt and Klapper, 2013)[4]. Hence, governments in both developed and developing countries are endeavoring to ensure a high level of financial inclusion. In 2010, the leaders of G20 countries launched the Global Partnership for Financial Inclusion (known as the GPFI), aiming at enhancing financial inclusion in each member country. At the same time, the World Bank and the United Nations also recognised the importance of financial inclusion, to the point at which developing financial inclusion has been added to their agenda. By 2013, over 50 countries had made commitments to improving financial inclusion, and hopefully a universal access to basic financial services will be reached by 2020 (The World Bank, 2013). Moreover, the Chinese government has issued the Development Plan for Promoting Financial Inclusion (2016-2020) which indicates that developing domestic financial inclusion has become one of the main national strategies in China (State Council of the People's Republic of China, 2015). Under such circumstances, understanding the determinants of financial inclusion and its impact on the economy has become urgent for policy makers and scholars alike.

Amongst all emerging countries, China stands out as a special case. According to the World Bank Global Findex Database (Demirgüç-Kunt and Klapper, 2012), a representative cross-country database on financial inclusion, the latter can be measured along three dimensions,

[4] The mechanism behind this is discussed in the Section 2.3.1.

namely the ownership of an account at a formal financial institution (*formal account*), savings at a formal financial institution (*formal saving*) and the use of bank credit (*formal credit*). According to the Findex Database, in 2014, 79 percent of the surveyed Chinese adults had an account at formal financial institutions. This figure is much higher than the world average (61 percent). It is also higher than that of some other BRIC countries (68 percent of Brazilian adults, 67 percent of Russian adults, 53 percent of Indian adults, and 70 percent of South African adults are reported having a formal account). As for *formal saving*, 41 percent of the surveyed Chinese individuals had saved at formal financial institutions in the past year. The figure for other BRIC countries ranges from 12 percent (South Africa) to 33 percent (India). The *formal saving* figure in China is also much higher than the world average (22 percent). Hence, in terms of both *formal account* and *formal saving*, it seems that China has an extremely high financial inclusion level. The two percentages are even more impressive considering that China's GDP per capita only ranked 3rd place among all BRIC countries in 2014[5]. However, when it comes to the *formal credit*, China does not rank as well: Less than 9 percent of Chinese individuals surveyed in the 2014 wave of Findex obtained credit from formal financial institutions during the last 12 months, and only 16 percent of Chinese individuals reported having a credit card.

It is surprising that Chinese households have such a high level of bank account ownership and savings, but a very low level of formal credit attainment. It is therefore interesting to look at the determinants of specific measures of financial inclusion in the Chinese context. Moreover, as the growth of the Chinese economy has been mainly driven by exports and government investments in the past, promoting financial inclusion is regarded as a valid tool of boosting domestic consumption and stimulating the economy. This paper will therefore aim at answering

[5] In 2014, the GDP per capital of each of the BRIC countries was as follows: Russia, 13,902 USD; Brazil, 11,729 USD; South Africa, 6,472 USD; China, 7,587 USD; India 1,577 USD. This data is taken from the World Bank Database.

the following questions: What determines various components of financial inclusion in China? In addition, would an enhancement of financial inclusion in China be useful in order to boost domestic consumption, achieving one of the key current objectives of Chinese policy makers?

Probably due to limitations in data availability, only a few papers have looked at financial inclusion in China. Among these, Fungáčová and Weill (2015) find that higher income, better education, being male, and being older are positively related to financial inclusion. These results are generally consistent with the findings obtained in cross-country studies (Beck and Brown, 2011, Allen et al., 2012, Demirgüç-Kunt and Klapper, 2013). Apart from the widely recognized factors, Cull et al. (2016) find that political connections positively affect households' access to formal finance in rural areas but not in urban areas, and a larger social network is positively associated with access to informal finance. Li et al. (2016) analyse both the demand and supply of bank credit and find that political connections (i.e. whether or not the household head is a member of political party) contribute to a higher credit demand, as well as a higher likelihood of being granted credit by banks in China.

This work makes the following contributions to the literature. Firstly, motivated by the facts that informal financing has been found to play an important role in boosting growth in the private sector in China (Allen et al., 2018, Cull et al., 2015a, Guariglia et al., 2011, Zhang, 2008) and formal financiers take into account small entrepreneurs' ability to raise informal finance when making lending decisions (Degryse et al., 2016), I investigate the links between informal financing and several dimensions of financial inclusion at the household level. Specifically, I proxy financial inclusion through bank accounts and credit cards ownership, having obtained formal loans, and through a composite index which denotes the possession of at least one of the three above mentioned indicators. To the best of my knowledge, this issue has been investigated in very few studies (Fungáčová and Weill, 2015, Cull et al., 2015a, Sui and Niu, 2018) and none of them has looked at the intertwined relationship between having informal and formal finance. Secondly, for the first time in the literature, I test whether a high level of financial inclusion may contribute to an increase in household consumption. Thirdly, this study is the first to take into account "voluntary exclusions", whereby households may not use certain financial services simply because they do not need them and are therefore voluntarily excluded from financial markets.

Based on a set of specifications estimated with linear probability models (LPM), Probit and OLS specifications, I firstly find that having informal loans is positively associated with the *formal credit* indicator of financial inclusion, but negatively associated with ownership of bank accounts and credit cards. This result is consistent with Allen et al. (2018) who find both complementarity and substitution effects between informal and formal financing at the firm-level in China. Additionally, I observe that, with the exception of credit card holding, the links between informal finance and financial inclusion tend to be larger and/or more prevalent for rural households. After controlling for the potential endogeneity of households having informal finance, the positive association between household's informal and formal loans becomes insignificant but the negative association between informal finance and other financial services remains significant. I also find that, in line with other studies on financial inclusion in China and other countries (Beck and Brown, 2011, Allen et al., 2012, Demirgüç-Kunt and Klapper, 2013, Cull et al., 2015a), households with younger and better educated heads, higher income, lower risk aversion, and larger family size are more likely to exhibit higher financial inclusion. Finally, I find that financial inclusion is generally associated with a higher level of consumption.

The remainder of the paper is organized as follows: Section 2.2 provides a brief introduction of the characteristics of the Chinese economy. Section 2.3 reviews the literature on financial inclusion and financial constraints (which can be seen as a form of financial exclusion) at the household level. Section 2.4 develops the main hypotheses. Section 2.5 presents the data and summary statistics. Section 2.6 illustrates the baseline specifications and estimation methodology. Section 2.7 describes the empirical results. Section 2.8 addresses the issue of endogeneity and Section 2.9 concludes.

2.2. The Chinese economy

2.2.1. The unbalanced economy: low domestic consumption and high saving rates

Consumption, along with export and investment, is one of the main engines of economic growth for a country. A healthy economy is characterised by a good balance between these three components of GDP. However, the Chinese economy is far from balanced. Over the last decade, the share of consumption dwindled, while the share of investment kept rising. In 2013, the share of investment in China's GDP reached 50 percent, much higher than the 22 percent world average and the 19 percent average of advanced economies[6]. Over-investment results in a concern of overcapacity in the industrial sector[7].

By contrast, the share of private consumption to GDP has been decreasing in recent years (Orlik and Chen, 2015). This share was 61 percent in 1990 and 58 percent in 1998 (Zhang and Wan, 2004). Yet, in 2013, it was only 38 percent. China's share of consumption to GDP stands as an outlier compared to other countries (see Figure 2.1). This evidence suggests that the Chinese economy needs to be rebalanced, which is a concern for policy makers.

On March 5th 2016, Li Keqiang, the Premier of the State Council of the PRC delivered the Report on the Work of the Government at the Fourth Session of the 12th National People's Congress of the PRC (State Council of the People's Republic of China, 2016). In this Report, strengthening the role of consumption in promoting economic growth has been emphasized again as one of the major areas of work for the Chinese government. In fact, promoting

[6] This data is taken from Bloomberg.
[7] For instance, with reference to the construction industry, some cities in China contain massive amounts of unsold properties, which transform them into "ghost towns" (Orlik and Chen, 2015).

consumption and rebalancing the economy have been added to the annual government work plan since 2008.

The low domestic consumption in China goes hand in hand with a massive saving ratio. Even under the environment of worldwide recession, in recent years, China's saving ratio has kept rising. At the national level, China's gross saving rate has been at around 50 percent for a decade.[8] This figure is at least twice as large as that of OECD countries. At the household level, Chinese households save a large proportion of their disposable income indicating that their behaviour is highly inconsistent with the Life-Cycle Hypothesis (LCH) where households dissaving in later life is predicted. This is referred to as the *"Chinese saving puzzle"* (Modigliani and Cao, 2004). In 2013, the average household saving rate in China was 38 percent, dramatically higher than that of OCED countries[9].

Several reasons have been proposed for the high saving ratio characterising China. Among these, the precautionary reason is a leading one. Before the reform, all workers were guaranteed permanent employment by the state sector, together with housing, coverage of all medical and educational expenses, as well as pensions. This was known as the 'iron rice bowl' (He et al., 2018). After the reform, which led to the privatisation of the economy, all these benefits were lost and people's jobs became much more uncertain. According to He et al. (2018), this uncertainty led to a rise in precautionary savings, which can explain 30 percent of the rise in savings over the period 1995-2002. Precautionary saving in China is magnified by the fact that people find it difficult to borrow via financial markets. Hence, saving is a convenient instrument to ensure they can sustain their current consumption level in the presence

[8] These data are taken from the World Development Indicator, the World Bank Data Library.
[9] These data come from OECD (2016), Household savings (indicator). doi: 10.1787/cfc6f499-en (Accessed on 26 May 2016).

of negative income shocks. Several other explanations have been put forward to explain the high and rising saving ratio in China. Among these, Feng et al. (2011) focus on the weaknesses of the pension system; Wang and Wen (2012), on the rising house prices; Barnett and Brooks (2010), on the increasing health and education expenditures; Meng (2003) and He et al. (2018), on the rising unemployment risks; Wei and Zhang (2011) on the increasing sex ratios; and Zhu et al. (2014), on the declining number of children that followed the introduction of the one child policy. Under these circumstances, promoting financial inclusion could help enhancing domestic consumption, as it would reduce the need to save for precautionary reasons. This is certainly one of the reasons why policy makers in China are paying increasing attention to financial inclusion.

2.2.2. Informal financing and co-funding in China

As in other countries with underdeveloped formal financial markets, both Chinese enterprises' and individuals' financial decisions make heavy use of informal financing. Informal financing in general is loosely defined as all finance sources provided by agents different from banks and other formal financial institutions.

According to Tsai (2004b), those sources include trade credit, borrowing from families or friends, private money houses, pawnshops and others. Although the exact amount of informal financing is difficult to calculate, as some of it may involve illegal activities, a conservative estimation shows that informal financing in China accounts for at least one quarter of all financial transactions (Tsai, 2004a). Allen et al. (2005) suggest that informal financing plays a crucial role in supporting the growth of private firms and consequently boosting economic growth. Allen et al. (2018) argue that when the banking industry is more developed, the effect of informal financing on firm growth diminishes. Addtionally, their results show that informal financing is more prevalent in cities where firms have more access to bank credit, siggesting that the two forms of finance are complements. Firms thus rely on both channels in order to finance their activities, which is referred to as co-funding (Zhang, 2008, Degryse et al., 2016). Cull et al. (2015a) argue that co-funding is also common for Chinese households. Those who have access to formal finance also hold informal finance. In their sample which was taken from the 2013 wave of China Household of Finance Survey, 48.3 percent of Chinese households have some loans, but only 16.2 percent of them have bank loans while 40.9 percent have borrowed from informal sources. This indicates that Chinese households use both formal and informal financing, and are more likely to borrow from informal sources.

Compared to bank credit, informal financing is easier to obtain since it is typically based on reputation or trust without any collateral requirements. The cost of informal financing depends on the sources: lending from family or friends is normally with no or low interest, while lending from private money lenders involves very high interest rates. Allen et al. (2018) show that 6.7 percent of the new investment and 7.9 percent of the working capital of the firms in their sample comes from trade credits and loans from families or friends. However, as firms' activities usually involve a considerable amount of investment, loans from family or friends are unlikely to be sufficient.

By contrast, the percentage of households relying on informal sources from families or friends is generally much higher than that of firms. Turvey and Kong (2010) document that 52 percent of all Chinese rural household's borrowing comes from family members and/or friends. Similarly, based on the 2011 CHFS, 25.5 percent of the Chinese households have at least one informal loan (whilst less than 14.2 percent of them have a formal bank loan), and over 90 percent of the informal loans is from family members and friends. Households seem therefore to make a much larger use of informal financing than firms. It is therefore particularly interesting to look at links between formal and informal financing for Chinese households.

2.3. Literature review

2.3.1. Merits of an inclusive financial system

The finance-growth nexus has been widely discussed in the literature. A number of theoretical and empirical studies have found a positive link between financial development and growth (Beck et al., 2007b, Bruhn and Love, 2014, Goldsmith, 1969, Honohan, 2004, Levine, 1997). Goldsmith (1969) is the first well-known work in this field. Using data on 35 countries from 1860 to 1963, he finds that rapid economic growth is always accompanied by an above-average rate of financial development. Levine (1997) reviews a large number of papers and concludes that there is a strong and positive link between financial development and economic growth, as financial development facilitates trading, diversifies risks, helps to better allocate resources, mobilizes savings and facilitates the exchange of goods and services. Beck et al. (2007a) confirms the positive linkage between financial development and economic growth. Additionally, they find that financial development also has the additional effect of reducing inequality and poverty by boosting the aggregate income growth of the poor. Their findings are consistent with Honohan (2004), who find that financial development fosters sustainable economic growth.

Using provincial data from China over the period 1989-2003, Guariglia and Poncet (2008) examine the effects of a set of indicators of financial development on different proxies of economic growth. They find that the indicators measuring the degree of market-driven financing helps promote gross domestic product (GDP) and total foctor productivity (TFP) growth, as well as capital accumulation, while other indicators measuring the level of state interventionism in finance are generally negatively related to economic growth. Their findings suggest that financial distortions place obstacles on economic growth. Using data from 286 cities over the period 2001-2006, Zhang et al. (2012) find a positive relationship between various measurements of financial development and economic growth after controlling for other factors that may affact economic growth.

The above mentioned strong relationship between financial development and economic growth has convinced policy makers and researchers of the benefits of promoting financial inclusion. It is in fact widely recongised that an inclusive financial system contributes to a deeper and broader development of the financial sector and consequently to higher economic growth. Intuitively, with better access to financial services, individuals are able to allocate their assets in a more efficient way and firms, especially small enterprises, are able to grasp any promising growth opportunities (Demirgüç-Kunt and Klapper, 2013).

Apart from its impact on economic growth, an inclusive financial system also contributes to mitigating persistent income inequality and poverty. Honohan (2008) observes a positive correlation between financial inclusion and gross national income (GNI) per capita in 160 countries. Based on an experiment in rural India, Burgess and Pande (2005) find evidence that the state-led expansion of bank branches in unbanked areas significantly increases credit and continuously reduces povery. Bruhn and Love (2014) take advantage of the fact that over 800 bank branches opened in 2002 in Mexico. Treating this fact as a natural experiment, they find robust evidence on the positive impact of the improved access to financial services on poverty reduction. Similar results are found in Brune et al. (2011) who focus on rural Malawi, and Allen et al. (2013), who investigate the Kenyan context.

2.3.2. Measurements of financial inclusion and its determinants

Due to the importance of financial inclusion, an increasing number of studies has been focusing on its measurement and determinants. There is much less consensus on the former than the latter. Literature on the measurement of financial inclusion can be roughly divided into two parts.

The first stream includes Honohan (2008), Allen et al. (2012), Demirgüç-Kunt and Klapper (2012, 2013) and Fungáčová and Weill (2015). These authors consider direct indicators of financial inclusion such as the use of formal accounts, saving behaviour, and the availability of credit. Specifically, Honohan (2008) uses the percentage of households having accounts at formal financial intermediaties within one country as an indicator of this country's financial inclusion level. Allen et al. (2012) use the ownership of a bank account, the usage of the account to save, and the frequency of using this account as indicators of both country- and individual-level financial inclusion. In addition to the use and ownership of a bank account, Demirgüç-Kunt and Klapper (2012, 2013) and Fungáčová and Weill (2015) also use *formal saving* and *formal credit* as indicators. Being based on multiple indicators, their approach presents a relatively more comprehensive picture of financial inclusion. However, the pitfall of using multiple indicators is that different indicators may behave differently. Thus, the evaluation of the overall financial inclusion level amongst countries or within a country becomes arbitrary and misleading as the ranking would highly depend on the indicator chosen.

The second stream of literature includes Sarma (2008), Mialou et al. (2017), and Park and Mercado (2015). These authors compute a composite financial inclusion index (FI index). By combining various information on penetration, availability, and usage of formal financial services, they calculate a composite index presenting the level of financial inclusion for each country. Specifically, Sarma (2008) measures a FI index as the normalized distance from the ideal value (full financial inclusion) to the actual value in a n-dimensional space where each financial inclusion dimension denotes one axis in this space. He uses the number of bank accounts per 1,000 adults, the number of bank branches per 100,000 adults, domestic credit (as percent of GDP) and domestic deposits (as percent of GDP) as four dimensions of financial inclusion. He then standardizes each dimension of the index, so that the maximum value of each dimension is 1 and the minimum value is 0. In the four-dimensional space, the ideal value (full financial inclusion) is thus the point I=(1,1,1,1), presenting the achievement in all dimensions. The financial inclusion index is calculated as the normalized inverse of the distance from each country's actual situation (the actual point in the space) to the ideal value. Normalization ensures the value of the FI index is between 0 and 1, and taking the inverse makes sure that higher values of the FI index represent higher financial inclusion. This method is closely followed by Park and Mercado (2015). Based on four dimensions of financial inclusion, namely the number of ATMs per 1,000 square kilometers, the number of branches of other depository corporations (ODCs) per 1,000 square kilometers,[10] the total number of resident household depositors with ODCs per 1,000 adults, and the total number of resident household borrowers with ODCs per 1,000 adults, Mialou et al. (2017) take advantage of the factor analysis (FA) method in order to reduce the dimensions of financial inclusion and obtain a single index for each country in their sample.

The rankings based on the calculated financial inclusion scores from all methods mentioned above are very similar. In particular, developed countries' financial inclusion is

[10] According to Mialou et al. (2017, p.9): "*The ODC sector includes commercial banks, credit unions, saving and credit cooperatives, deposit taking microfinance (MFIs), and other deposit takers (savings and loan associations, building societies, rural banks and agricultural banks, post office giro institutions, post office savings banks, savings banks, and money market funds*)".

significantly higher than that of developing countries and wealthier countries are generally associated with higher financial inclusion. Compared to multi-indicators of financial inclusion, indices provide a more convenient way to compare financial inclusion across countries. However, one problem with the use of a composite index of financial inclusion is that the weights chosen for each component in the index could be arbitray. Countries ranked higher in dimensions with higher weights are more likely to obtain a higher FI index.

As for determinants of financial inclusion, findings in the literature are fairly consistent. At the country level, wealthier countries are associated with higher financial inclusion (Honohan, 2008, Allen et al., 2012, Demirgüç-Kunt and Klapper, 2012, Demirgüç-Kunt and Klapper, 2013, Mialou et al., 2017, Park and Mercado, 2015, Sarma, 2008). The sharp disparities in financial inclusion between developed and developing economies appear no matter what indicator is used. At the individual level, being male, better educated, wealthier and/or older are associated with higher financial inclusion (Cull et al., 2015a, Demirgüç-Kunt and Klapper, 2013, Fungáčová and Weill, 2015). Due to recent developments in detailed micro-level datasets, financial literacy is also found associated with higher financial inclusion (Cull et al., 2015a, Sui and Niu, 2018).

2.3.3. Liquidity constraints

Pirior to the widespread recognition of financial inclusion, liquidity constraints have been widely studied in the literature. These constraints can be seen as a typical phenomenon of financial exclusion. Hall and Mishkin (1980) and Zeldes (1989) observe that around 20 percent of U.S. households deviated from their optimal consumption indicated by the standard Life-Cycle Hypothesis. They attribute this deviation to the existence of liquidity constraints. Later, the presence of liquidity constraints in the US has been confirmed by Jappelli and Pagano

(1989), Jappelli (1990), Garcia et al. (1997), Engelhardt (1996) and Jappelli et al. (1998). Among these, Jappelli (1990) is the first to study the determinants of liquidity constraints at the household level. He uses data from the 1983 US Survey of Consumer Finances (SCF) and looks into the relationship between consumers' characteristics and the probability of being excluded from bank credit by applying a logit model. He identifies those who have been rejected credit by formal financial institutions as financially excluded. The result shows that consumers with lower current resources face more liquidity constraints. Being young indicates the lack of a credit record which may tighten one's credit constraints, but it also indicates less demand for consumption and higher future labour income compared to consumers in other age groups. Thus, the effect of age is ambiguous.

Inspired by Jappelli (1990), Garcia et al. (1997) also attempt to investigate the determinants of being liquidity constrained in the US. Their findings suggest that, in addition to income and wealth, other social and demographic variables such as race, sex, and marital status also have an impact on determining access to financial services.

Those studies have shown that in addition to age, income, education, and gender, other factors also affect the likelihood of households being included/excluded in/from financial services. However, there is little evidence on what such factors might be. This work potentially fills this gap and provides a more detailed description of financial inclusion in the Chinese context.

2.3.4. Literature on China

Although Chinese policy makers have added 'promoting financial inclusion' on their agenda, little is known about Chinese households' degree of financial inclusion. Only a small number of studies have focused on micro level evidence on the determinants of financial inclusion in China, and none of them takes into account the “voluntary exclusions” issue.

Using data from the 2011 World Bank Global Findex Database, Fungáčová and Weill (2015) provide some information on financial inclusion in China and make some comparisons between China and other BRIC countries. They find that the limited financial inclusion in China is mainly due to the limited access to formal credit. They argue that, as a consequence of this, informal credit from relatives or friends (rather than formal credit from banks) is the main financing source for Chinese households. However, due to data limitations, Fungáčová and Weill (2015) only look at the role of a limited range of individual characteristics in affecting financial inclusion (e.g. age, gender, income and education). Other important potential variables such as region of residence, family size, employment status, and marital status are omitted in their study.

Using the 2013 wave of the China Household Finance Survey in 2013, Cull et al. (2015a) analyse the links between household characteristics such as wealth, social networks, political connections, financial and economic literacy, and access to formal and informal finance. They conclude that younger, less educated households with lower income, limited financial knowledge, and larger family size are less likely to have access to formal finance and are more likely to rely on informal finance. These results suggest that Chinese households face dual credit markets.

Cull et al. (2016) specifically study the link between social capital and access to credit, as well as its implications for households’ consumption levels. Based on the 2013 wave of the China Household Finance Survey, they define households’ social capital in two ways: private social networks and membership to the Communist Party. They document that party affiliation is linked to a higher level of consumption in rural areas, but the positive impact is not resulted from a better access to credit markets.

Using the same dataset, Sui and Niu (2018) study the determinants of household's ownership of bank deposits, risky financial assets and credit cards. They further test the differences in financial service usages between urban and rural households. They document the existence of both demand side and supply side barriers to financial inclusion in China. On the demand side, socioeconomic status (SES) affects households' access to financial services. Being poor and having less education are associated with lower demand for finance. On the supply side, in less-developed areas of China, households have less availability and accessibility to financial services compared to those living in financial developed areas, leading to a low usage of financial services in less developed areas. In addition, Sui and Niu (2018) find that improving financial infrastructures may have larger impacts on promoting financial inclusion in less-developed areas than in developed areas.

Also using the 2013 wave of CHFS, Li (2018) studies the importance of relative income in determining households' financial inclusion in China. The author argues that income comparisons with peers may increase household debts. In particular, households with low income are more likely to apply for bank credit than those with high income due to peer comparisons. Among all applicants who obtained bank credits, those with low income increase education spending more than the rich. This may indicate a "tunnel effect", in which the poor are inspired by the rich's economic success and thus invest more in human capital via borrowing. The author further documents that if the "tunnel effect" is the main drive of the poor applying for bank credits, indebtedness of poor household is less concerning, and developing financial inclusion will help the poor improve their socioeconomic situation.

Zhang and Wan (2004) show that liquidity constraints are responsible for the decline in both the level and growth of consumption over the period 1961-1998. Liquidity constraints and uncertainty mutually reinforce each other's effect, hence accelerating the decline in consumption. Due to the presence of binding liquidity constraints, Chinese households cannot borrow freely. As a consequence, they may cut down their consumption in the presence of uncertainty. However, this study is only conducted at the aggregate level.

Using data collected by the Ministry of Agriculture of the PRC, which covers 1,000 households from 2003 to 2009, Li et al. (2013) find that 61.5 percent of Chinese rural households in their sample are credit rationed, and that this rationing leads to a decrease in consumption. Smilarly, using a survey consisting of 743 hosueholds, Li et al. (2016) estimate that 54.9 percent of rural households in the Jiangxi Province are credit constrained. They also find that households with credit constraints have 7.3 percent less consumption expenditure compared to those without. These findings suggest that reducing household's credit constraints/increasing financial inclusion may be a valid tool for boosting China's domestic consumption.

In conclusion, to the best of my knowledge, only few studies look at the determinants of financial inclusion in the Chinese context. Furthermore, none of these studies focus on the relationship between informal financing and financial inclusion, and only few of them look at links between financial inclusion and household consumption. Finally, none of these studies takes into account "voluntary exclusions" from credit markets. This work thus extends the existing literature in several dimensions: for the first time in literature, I test whether having informal finance facilitates gaining formal finance; I drop households who voluntary exclude themselves from financial markets to alleviate the self-selection issue; and I further test the extent to which financial inclusion is associated with household consumption. These findings could potentially help Chinese policy makers reach their objectives of promoting financial inclusion and stimulating domestic consumption.

2.4. Hypotheses

2.4.1. General hypothesis

Previous studies, which focus both on firms (Zhang, 2008, Allen et al., 2018, Degryse et al., 2016, Ayyagari et al., 2010) and households (Cull et al., 2015a), find that informal and formal financing co-exist in China. Among these, Allen et al. (2018) argue that informal and formal financing can be either complements or substitutes for firms, depending on firms' characteristics, while Ayyagari et al. (2010) question the traditional view of informal finance complementing formal finance systems and also contributing to firms' growth. To the best of my knowledge, although informal financing is widely used by Chinese households (Fungáčová and Weill, 2015), no paper has tested the interactions between informal and formal financing at the household level. Intuitively, informal finance may crowd out households' needs for formal financial services. In other words, it may substitute to formal finance. However, it may also serve as collateral, making it easier to obtain longer-term financing such as bank loans, which would lead to a complementarity between the two sources of finance. In line with this argument, Degryse et al. (2016) find that, in the Chinese context, formal financiers take into account small entrepreneurs' ability to raise informal finance when making lending decisions.I therefore hypothesize that:

H1: Informal financing may serve as a complement to long-term financial services such as bank loans, but as a substitute to other financial services.

2.4.2. Hypothesis on the effect of financial inclusion on households' consumption

As China is experiencing a slow-down in exports as a consequence of the recent financial crisis, and an overheating of the economy due to excessively high investment, it is important for the economy to be rebalanced through an increase in domestic consumption. This can be achieved by increasing domestic consumption and/or reducing the high saving rates that characterises the Chinese economy (Meng, 2003, Barnett and Brooks, 2010, Wei and Zhang, 2011, Wang and Wen, 2012).

The very high saving rate/low domestic consumption characterizing Chinese households could be due to a low level of financial inclusion. If this were the case, policies aimed at boosting domestic consumption should enhance financial inclusion. In order to see whether or not this is the case, I test the following hypothesis:

H2: Financial inclusion is positively associated with household consumption.

2.5. Data and summary statistics

2.5.1. The China Household Finance Survey

This work largely relies on the 2013 wave of the China Household Finance Survey (CHFS), one of the most representative and highest quality micro-level datasets in China. The dataset is published by the Survey and Research Centre of China Household Finance at the Southwestern University of Finance and Economics. It surveys 28,100 households from 29 Chinese provinces/municipalities and contains detailed information on their income, assets, debt, and expenditure as well as their social and demographic characteristics. The baseline survey is conducted in 2011 with only 8,438 households being interviewed. In addition, the 2011 wave lacks important information needed for my analyses, such as household heads' financial literacy. To reduce the concern for outliers with extreme high or low household income and wealth, I drop observations with income/wealth lower than the 1st percentile or higher than the 99th percentile of the income/wealth distribution.

2.5.2. Indicators of financial inclusion

I use four indicators as proxies for financial inclusion, namely the ownership of bank accounts (*Account*), the ownership of credit cards (*Credit*), the possession of bank loans (*Floan*) and having either one of the three above-mentioning financial services (*Inclusion*).

In the CHFS questionnaire, each respondent is asked the following sets of questions. The first relates to credit cards and are formulated as follows: "*Does your family have a credit card? Inactive credit cards are not included*." and "*When you and your family shop, what is your typical method of payment?*" Those who answer "*yes*" to the former question and "*credit cards*" in the latter question are identified as having a credit card. For these respondents, the *Credit* dummy equals one. For those who answered "*No*" to the former question or answered using other methods of payment when shopping in the latter question, the *Credit* dummy equals zero.

The second set of questions relates to formal bank loans and read: "*Do you currently have any loans for your industrial/commercial activities?*", "*Currently, has your family borrowed money to purchase, improve, remodel, or expand your home?*", "*Did your family take bank loans to buy your cars?*" and "*Have any family members taken out student bank loans?*" Those who answer "*yes*" in at least one of these questions are identified as having a formal bank loan. The *Floan* dummy will therefore take value one for these respondents otherwise it equals zero.

The third set of questions relates to bank accounts: "*Does your family currently have RMB denominated checking accounts?*" and "*Does your family currently have outstanding RMB time deposits?*" Those who answer "*yes*" to at least one of the above questions are identified as having a bank account. For these respondents, the *Account* dummy equals one otherwise it equals zero.

Furthermore, I generate a combined indicator of overall financial inclusion based on the three individual indicators mentioned above (*Inclusion*). *Inclusion* equals one if the household possesses at least one of the three financial instruments discussed above (i.e. bank account, credit card, or formal loan), and zero otherwise.

These indicators can be justfied as follows. Evidence found in the Global Findex Database (Demirgüç-Kunt and Klapper, 2012) suggests that financial exclusion in China is mainly due to the lack of formal credit. This evidence is confirmed by Fungáčová and Weill (2015). I therefore construct two indicators to proxy for financial inclusion in formal credit markets: the ownership of a credit card (*Credit*) and having obtained loans from formal financial institutions

(*Floan*). Data reported in the Global Findex Database 2011 reveal that only 7 percent and 8 percent of Chinese adults have a credit card and a formal loan respectively. The *Floan* indicator is consistent with similar indicators used in Demirguc-Kunt and Klapper (2012, 2013). The *Credit* indicator, on the other hand, which represents the ownership of a credit card, has not yet been used in the literature.[11] Additionally, I also use a third indicator, *Account*, which measures the ownership of a formal bank account and has been widely used in studies on financial inclusion (Allen et al., 2012, Demirgüç-Kunt and Klapper, 2012, Fungáčová and Weill, 2015). Finally, I construct the indicator *Inclusion* to measure the possession of either one of the three above-mentioning formal financial services.

2.5.3. Use of informal finance

My primary research interest is distangling the relationship between informal and formal finance at the household level in China. In paticular, I want to test the extent to which informal finance is used as an alternative to formal finance, in the absence of a well-developed financial market. Following Cull et al. (2015a), I construct a dummy variable "*Infloan*" which is equal to one if the household currently has at least one loan from friends, relatives, co-workers, or other non-banking financial institutions, and zero other wise. In the CHFS, respondents are asked whether they make use of informal loans to finance households' business or agricultural projects, purchases or refurbishments of houses/flats, purchases of vehicles, and education or training programmes. These items are consistent with the ones used for constructing *floan*. It is also worth mentioning that, according to the CHFS data, more than 80 percent of the informal loans are obtained from family members or friends with no collateral required and no interest

[11] The percentage of adults having a credit card is reported in the World Bank Global Findex Database. However, the determinants of having a credit card have not been studied.

charged. Moreover, 79 percent of those who have at least one informal loan borrow because of housing-related events.

2.5.4. Other control variables

Following Cull et al. (2015a) and Fungáčová and Weill (2015), the control variables include household heads' age, education level, work and marital status, household income and net wealth, household size, and home ownership. In the context of China, I also include an indicator for political access (*party*). This is a dummy variable denoting whether or not the household head is a communist party member. Guariglia and Mateut (2016) find evidence for political affiliation contributing to alleviating financial contraints in Chinese firms. Similarly, Cull et al. (2015b) find that firms with non-government-appointed CEOs face higher financial contraints. It is thus reasonable to assume that households whose heads are members of the ruling party may have better access to formal financial services in China. This is later confirmed in Cull et al. (2016).

Similar to Cull et al. (2015a) and Sui and Niu (2018), I also control for the level of financial literacy of household heads. In the 2013 wave of the CHFS, there are three questions relating to respondents' basic financial literacy. These questions test the respondents' basic financial knowledge regarding interest rates, inflation and portfolio risk management. I construct a variable *grade* which takes a value between zero (if the respondent answers no question correctly) to three (if the respondent answers all questions correctly). This represents the household's financial literacy level. In addition, I include a variable *risk_averse* based on respondents' answer to the question "*Do you prefer receiving 4,000 RMB for sure to receiving 10,000 RMB with 50 percent probability?*" to reflect household heads' risk attitude. Those who prefer receiving 4,000 RMB are identified as risk averse heads. In this case, the dummy *risk_averse* equals to one, otherwise it equals zero.

2.5.5. Measurements of household consumption

After studying the determinants of financial inclusion in China, I further test the possible impact of financial inclusion on Chinese households' consumption. To this end, I calculate household total non-durable consumption. The items included in non-durable consumption are the following: expenditure on food at home and out of the home, utility bills, purchases of household items, fees for hiring cleaners/babysitters/servants, commuting costs, cellphone and internet bills, clothes, heating bills, travelling expenditure, education and training fees, and healthcare expenditure. I do not include durable consumption such as the purchase of antiques and luxury goods, cars, furniture and electronic devices because the incurrence of these fees is likely to be volatile across years. Moreover, expenditure on durable items can be seen as a form of investment. I drop observations with total non-durable consumption higher than the 99th percentile or lower than the 1st percentile of the consumption distribution to reduce the concerns for outliers.

2.5.6. Dealing with voluntary exclusions

It is of great importance to differentiate between voluntary and involuntary exclusions (Demirgüç-Kunt et al., 2008). However most of the studies in this field do not take this distinction into consideration.

Figure 2.2 shows the distinctions between voluntary and involuntary exclusions. Boxes in grey denote access to financial services for individuals, while boxes in white show no access to formal financial services. Voluntary exclusions and involuntary exclusions both relate to non-users of formal financial services. However, not using financial services is not necessarily associated with no access to financial services. Among non-users, voluntary exclusions result from not needing to use financial services or, in some regions, from religious reasons. Adults may choose to be excluded from financial services because they do not need to use these services. Others may actually be eligible to use financial services, but for religious reasons, may decide not to do so. These exclusions are self-determined: Voluntary non-users may have in fact access to formal financial services, but choose not to use them[12]. By contrast, involuntary exclusions refer to people who demand financial services but do not have access to them. Reasons for the exclusions could be that these individuals have insufficient income or using financial services is too costly for them.

From the policy makers' perspective, voluntary exclusions are not problematic because they are driven by lack of demand (Demirgüç-Kunt et al., 2008). Policy makers mainly focus on how to eliminate barriers for those who have no access to financial services, despite wishing to use them.

For these reasons, I omit voluntary exclusions from the analyses. The CHFS enables me to do so. For individuals who do not have a formal loan (including any aspect of agricultural/business related loans, mortgages, and vehicle related loans), a follow-up question is asked, namely " *Why don't you have one?*" Some individuals answer they do not have formal loans because of "*No need*". I thus idenfity observations who answered "*No need*" in any one of the three components of *Floan* as voluntary exclusions.

[12] One concern is that those who voluntarily excluded may not apply for financial services because they perceive rejections if they were applying for one. Fortunately, the CHFS enables me to identify those "discouraged" borrowers and these observations are kept in the final sample.

Focusing on the *Credit* indicator, individuals who do not currently use a credit card are asked: "*Why don't you have a credit card?*" Some of them answer: "*Like spending cash*". I identify these responses as voluntary exclusions and exclude them from the corresponding *Credit* analysis. I also exclude those who "*like spending cash*" and/or have "*no need*" for a loan from the regressions with dependent variable *Inclusion*.

After omitting voluntary exclusions, the sample size drops from 28,100 observations to 20,105 for *Credit*, and from 14,515 for *floan* and 10,868 for *Inclusion*. Appendix 2.2 investigates differences in the marginal effects of regressors including and excluding those voluntary exclusions. It also looks at the determinants of voluntary exclusions.

2.5.7. Summary statistics

Table 2.1 presents the means and standard errors of all variables used in the present study. Detailed variable definitions are provided in Appendix 2.1. Considering the wide existence of disparities between urban and rural areas in China, Table 2.1 also reports the mean differences between urban and rural subsamples.

We can see clear and statistically significant urban-rural differences across all measures of financial inclusion. Specifically, urban households are more likely to own bank accounts, credit cards and bank loans, compared to their rural counterparts. The overall financial inclusion is also higher for urban households. The differences in the four financial inclusion indicators between urban and rural households are highly statistically significant. The mean of non-durable consumption for the rural sample is much smaller than that of the urban sample. The difference is as high as 16,823 RMB and significant at the 1 percent significance level. As for the use of informal finance, the data also highlights that a higher proportion of rural households hold informal loans compared to urban households. It is also worth mentioning that the percentage of households having an informal loan is higher than that of having a formal loan for both urban and rural groups, suggesting a wide penetration of informal financing among Chinese households.

Table 2.1 also shows that the income and wealth disparity between rural and urban households is huge. The average income of urban households is more than double that of rural households. The average net wealth of urban households is three times as large as that of rural households. The high housing price in urban areas potentially contributes to this considerable difference in net wealth. Furthermore, compared to rural households, urban households generally have younger and more educated heads, a smaller family size, a lower probability of home ownership and a lower chance of being employed. Additionally, the two groups have similar risk attitudes. All differences between the two groups are statistically significant.

2.6. Specifications and methodology

2.6.1. Determinants of financial inclusion

Following Allen et al. (2012), Fungáčová and Weill (2015), and Cull et al. (2015a), I start by estimating a Probit model of the following type:

$$Pr\left(D_{ij} = 1\right) = \Phi(\alpha + \beta_1 Infloan_i + \boldsymbol{\beta_2 X_i} + \boldsymbol{\gamma P_i} + \varepsilon_i) \tag{2.1}$$

where D_{ij} (j=1, 2, 3, 4) presents the four financial inclusion indicators, i.e. *Account*, *Credit*, *Floan*, and *Inclusion* for household *i*. $\boldsymbol{X_i}$ is a set of characteristics of household *i* and $\boldsymbol{P_i}$ is a set of provincial dummies for household *i*. Considering the main component of *Floan* is mortgages, I exclude *Homeownership* from the *Floan* regressions. I also exclude *Homeownership* from the regressions explaining financial inclusion in general, since *Floan* is a major component of *Inclusion*. ε_i is an idiosyncratic error term.

I estimate Equation 2.1 using a Probit model as the dependent variables are all binary. In line with H1, I expect the marginal effect of *Infloan* to be positive for *Floan*, but negative for *Account*, *Credit* and *Inclusion*. The urban-rural distinction in utilising financial services are well-documented in Sui and Niu (2018). To take into account the urban-rural disparity, I estimate Equation 2.1 using the full sample, as well as the rural and urban subsamples separately.

Among basic households' characteristics, I control for age, education level, gender, marital and employment status of the household head, household income and wealth, household size and home ownership, risk attitude, financial literacy as well as social capital measured by whether or not the head is a communist party member. These variables are in line with those considered by Cull et al. (2015a) and Sui and Niu (2018). I expect households with older, better educated and employed heads, having higher income and a smaller household size to be associated with higher financial inclusion. I expect being risk averse to be associated with lower financial inclusion and household heads with a higher level of financial literacy to be associated with higher financial inclusion.

2.6.2. The effect of financial inclusion on household consumption

Next, I test the extent to which financial inclusion, measured in turn through *Account*, *Credit*, *Floan* and *Inclusion* contributes to household consumption. The merits of financial inclusion have been fully discussed in Allen et al. (2012), Demirgüç-Kunt and Klapper (2012), and Beck et al. (2007b), who focus on its effects on economic growth, as well as poverty and inequality reduction. Households with better access to financial services may be able to borrow money in case of financial difficulties, which should lead to a lower need for precautionary savings and, ultimately, a higher level of consumption. To empirically test the extent to which financial inclusion is associated with household consumption, I estimate the following models for the logarithm of household total non-durable consumption using ordinary least squares (OLS):

$$\log(TotalC) = \alpha + \beta_1 Account_i + \beta_2 Credit_i + \beta_3 Floan_i + \boldsymbol{\beta_4 X_i} + \boldsymbol{\gamma P_i} + \varepsilon_i \tag{2.2}$$

and

$$log(TotalC) = \alpha + \beta_1 Inclusion + \boldsymbol{\beta_2 X_i} + \boldsymbol{\gamma P_i} + \varepsilon_i \tag{2.3}$$

where $\boldsymbol{X_i}$ is a set of characteristics of household i and $\boldsymbol{P_i}$ is a set of provincial dummies for household i. ε_i is an idiosyncratic error term.

I estimate Equation 2.2 and 2.3 using the full sample, as well as the rural and urban subsamples, respectively. In line with H2, I expect $\beta_1, \beta_2, \beta_3$ in Equations 2.2 and β_1 in Equation 2.3 to be positive.

2.7. Main empirical results

2.7.1. Determinants of financial inclusion

Table 2.2 presents the marginal effects obtained from estimations of Equation 2.1. I observe that having an informal loan is associated with a 7.9 percent higher probability of having formal bank loans in the rural sample (column 9). The corresponding percentage in the urban subsample is 8.6 (column 8). One possible explanation for this finding is that informal borrowing might be seen as collateral by banks. This would suggest that, in China, households may rely on informal borrowing to obtain formal loans. This interpretation is consistent with Degryse et al. (2016) who show that formal financiers take into account entrepreneurs' ability of raising informal fundings when making lending decisions in the Chinese context. The marginal effect associated with *Infloan* is also significantly positive in the full sample (column 7). This indicates that having informal borrowing is associated with an 8.2 percent higher probability of having formal bank loans.

As for other financial inclusion indicators, namely *Account*, *Credit*, and *Inclusion*, they are generally negatively associated with the probability of having informal loans. Specifically, having an informal loan is associated with a 3.3 percent lower probability of having a credit card in the full sample (column 4). Similar results are obtained for the urban and rural subsamples (columns 5 and 6), and the substitution effect is larger for urban households. These findings can be explained considering that credit cards are used to cover shorter-term needs for financing and are relatively costly in the Chinese context. Hence, having informal loans reduces the use of credit cards. Furthermore, informal loans are associated with a 6.6 percent lower probability of having a bank account in the full sample (column 1), suggesting that cheap informal loans may reduce the demand for other financial services. Once again, similar results are found in both the urban and rural subsamples (columns 2 and 3), with the substitution effect being slightly larger for the latter. As for the general indicator of financial inclusion (*Inclusion*), it exhibits a negative and significant marginal effect both in the full and the urban samples (columns 10 and 11), indicating a negative association between informal financing and financial inclusion.

Focusing on the control variables, I find that age is negatively related to *Credit*, *Floan* and *Inclusion* for both rural and urban households. Yet, the magnitude of these associations is small. This is consistent with Cull et al. (2015a), and can be explained considering that older household heads may have limited awareness of financial services compared to their young counterparts[13]. These findings also show that household income and net wealth are both positively associated with the likelihood of financial inclusion. This effect is always larger in rural areas, except for the *floan*. This can be explained considering that rural households face stricter requirements on creditworthiness compared to urban households because information asymmetries are likely to be more prevalent in rural areas. Having secondary education or above is positively related with the probability of financial inclusion, while being illiterate is significantly associated with a lower financial inclusion. A better education level may increase the likelihood of credit applications being approved and thus it is positively associated with financial inclusion. These findings are in line with those from other countries.

[13] Several papers in the literature account for a non-linear relationship between age and financial inclusion (Jappelli, 1990; Allen *et al.*, 2012; Fungacova and Weill, 2015). However, the marginal effect associated with Age^2 was almost zero if added in my regressions. I thus excluded Age^2. It is interesting to note that Allen *et al.* (2012) and Fungacova and Weill (2015) find a non-linear relationship between age and financial inclusion. In particular, they find a positive relationship initially, which turns negative after a certain age. The negative correlation we observe between age and financial inclusion can therefore be explained considering that the average age in my sample is 50.08.

The marginal effect associated with *male* is negative and significant for *Credit*, *Floan* and *Inclusion*. This suggests that being male is associated with lower financial inclusion than being female. This contradicts Fungáčová and Weill (2015), according to which being female is associated with a 4.5 percent (2.5 percent) lower probability of having bank accounts (formal loans). These finding suggests that gender discrimination in obtaining formal financial services is not a concern in the Chinese context. The difference may be attributed to the comprehensive households' characteristics I control for. In Fungáčová and Weill (2015), only income, age, gender and education are considered due to data limitation. The relation they find between gender and financial inclusion may be driven by unobserved factors that are not controlled for such as households' risk attitude and financial literacy.

Being married is associated with a higher likelihood of having bank accounts, credit cards and bank loans. It is likely that households with married couples have higher needs of financial services compared to households with a single member. Interestingly, I also find that being widowed is positively associated with a higher likelihood of having credit cards and owning bank loans compared to household with single heads. Having a job is significantly associated with a higher likelihood of having credit cards. This may relate to the fact that being employed is normally one of the first requirements when applying for a credit card.

Being risk averse is negatively associated with the probability of having a credit card and/or formal loans. This may reflect a lower demand for credit among risk averse households. They may lack trust on banks and financial services. Financial literacy is highly and positively associated with all financial inclusion indicators, suggesting that better financial knowledge is associated with higher usages of financial services. Being a Communist Party member is related to a higher probability of having bank accounts, credit cards, and overall financial inclusion.

Consistent with Cull et al. (2015a), I also find that being a party member is significantly associated with a higher probability of having bank loans in the rural area. Lastly, in the full sample, the marginal effect associated with the rural dummy is negative and statistically significant for *Account*, *Credit*, and *Inclusion*, suggesting that being based in a rural area is associated with a lower level of financial inclusion. This can be explained considering that financial development is poorer in rural areas. However, the marginal effect on the rural dummy is positive and significant for the *Floan* regression, indicating the existence of anti-poverty programmes which favours rural areas in China.

In summary, the results show that Chinese households rely on financial services from both informal and formal sources, which confirms the existence of dual credit markets first proposed by Cull et al. (2015a). Informal loans act as substitutes for bank accounts and credit cards but seem to be complements to bank loans. However, endogeneity may arise due to other factors that are not controlled for in the model and may affect *Floan* and *Infloan* at the same time. I will discuss endogeneity of *Infloan* in Section 2.8.

2.7.2. To what extent is financial inclusion related to household consumption?

Estimates of Equation 2.2 to 2.3 are presented in Table 2.3. We can see that better access to financial services is generally positively related to household non-durable consumption. All marginal effects associated with the financial inclusion indicators are statistically significantly. More specifically, having bank accounts is associated with a 12.3, 9.9 and 13.1 percentage point higher consumption in the full, rural and urban samples, respectively (column 1, 3, 5). Similarly, having a credit card is associated with a 24.1, 29.4 and 25.4 percentage point higher consumption in the full, rural and urban samples, respectively (column 1, 3, 5). Having bank loans is associated with an 8.6, 13.2 and 7.8 percentage point higher consumption in the full, rural and urban samples (column 1, 3, 5). Finally, *Inclusion* displays positive and statistically significant marginal effects in all regressions (column 2, 4, 6). These findings strongly support H2. The findings suggest that, if financial barriers were cleared, household consumption would significantly increase.

As for other household characteristics, having a higher education level and better financial literacy, a higher income and net wealth, a larger household, being a communist party member, are all positively associated with household non-durable consumption. Age is negatively associated with total non-durable consumption. Being male and illiterate are also negatively associated with consumption, but such associations are not significant in the rural subsample. Having a currently working household head, being a home owner and being risk averse are significantly related to lower consumption level. In contrast to the predictions of the LCH, which indicates households dis-save in later life to maintain their consumption level, my results suggest that consumption declines with age. The underdeveloped pension system in China may be responsible for this phenomenon, together with the low generosity of the national health insurance schemes. Given the difficulties in getting support from formal financial institutions, older households tend to consume less to cover any unexpected expenditures that may arise in the future (Meng, 2003, Barnett and Brooks, 2010, Wei and Zhang, 2011, Wang and Wen, 2012, He et al., 2018).

2.8. Controlling for the endogeneity of *Infloan*

There is concern that *Infloan* may be endogenous. Households with less education, lower income and wealth are in fact more likely to show lower financial inclusion and thus may use informal finance more often. Moreover, households' social network and capital may affect both informal and formal finance of this household. I thus adopt an instrumental variable (IV) approach similar to Cull et al. (2016). Specifically, I use whether the household head has siblings to instrument the use of informal finance in the Equation 2.1. Households with siblings have more informal borrowing sources and thus are more likely to have informal loans. Cull et al. (2016) suggests that having siblings is a strong and significant predictor of informal finance use because it is pre-determined and it is unlikely to be endogenous once a comprehensive set of household characteristics are controlled for. I therefore use a binary variable *sibling_dum* indicating whether or not the household heads have siblings to instrument the ownership of informal loans in Equation 2.1.

I adopt two sets of estimators, namely the bivariate probit estimator and the special regressor (SR) estimator, to implement the IV approach using *sibling_dum* as the IV for *Infloan*. The IV probit estimator is not an option here because it can only be applied when the endogenous explanatory variable is continuous. The linear probability model (LPM) with IV is also not considered because its fitted values are not constrained to (0,1).

Wooldridge (2010) validates the use of a bivariate probit model to address the endogeneity of a binary explanatory variable in a probit model. The SR method was initially proposed by Lewbel (2000) and relies on a "special regressor" which is assumed to be exogenous and appear additively in the model. Following Dong and Lewbel (2015), I use *age* as the "special regressor" because it is arguably exogenous and continuous. The advantage of both these methods over the IV probit estimator is that they allow for a binary endogenous explanatory variable.

Table 2.4 reports estimated marginal effects of covariates by the bivariate probit and the special regressor estimators, respectively. All standard errors are obtained from 200 bootstrap samplings. For brevity, I do not report the marginal effects of other covariates other than *Infloan*. It is also worth noting that, marginal effects are directly comparable across specifications (Dong and Lewbel, 2015).

In the full sample, both special regressor and bivariate probit estimators give a larger effect of *Infloan* than the standard probit estimators. In Table 2.1, the marginal effect of *Infloan* estimated by the standard probit estimators was -0.07 for *Account*, -0.03 for *Credit*, 0.08 for *Floan* and -0.03 for *Inclusion*. Using the SR estimator, the corresponding marginal effect are 0.53, -0.35, -0.21 and -0.26 The estimated marginal effects on I*nfloan* obtained using the bivariate probit estimators are generally smaller than those obtained with SR: They are -0.27, -0.27, -0.12 and -0.16 for *Account*, *Credit*, *Floan* and *Inclusion*, respectively. The H1 is thus only partially supported due to the non-positive marginal effect associated with the *Floan*.

In the rural subsample, marginal effects estimated by the SR estimators are not statistically significant. In the bivariate probit model setting, having informal loans is associated with a 28.7 percent, 17.5 percent, 11.0 percent, and 19.6 percent lower probability of having bank accounts, credit cards, bank loans and overall financial inclusion. In the urban subsample, having informal loans is associated with a 42.4 percent, 55.4 percent, 32.0 percent and 25.6 percent lower probability of having bank accounts, credit cards, bank loans and overall financial inclusion using the SR estimators, with corresponding percentages being 26.2 percent, 31.0 percent 12.5 percent and 13.7 percent when using the bivariate probit estimators. These findings confirm that informal finance is a substitute of formal financial services. In addition, as marginal effects are comparable across specifications, I can compare the magnitude of the marginal effect of *Infloan* between the rural and urban subsamples. The substitute effect between informal loans and bank accounts as well as overall financial inclusion is larger in rural areas, while the substitution effect between informal loans and credit cards as well as bank loans is larger in urban areas. In addition, the substitute effect between *Infloan* and *Credit* is the highest in the urban subsample and the substitute effect between *Infloan* and *Account* is the highest in the rural subsample. This may indicate that, with the promotion of financial inclusion, the usage of bank accounts in rural areas and the ownership of credit cards in urban areas will experience the largest growth compared to other financial services.

It is worth mentioning that the positive association between having informal loans and having bank loans no longer exists in the new estimations, indicating the complementarity effect between informal and formal finance I found previously may have been due to an endogeneity bias. My finding is inconsistent with Allen et al. (2018) where evidence of the complementarity effect is found for Chinese firms. This suggests that the prevalence of informal finance among Chinese households may crowd out the need and usage of formal financial services.

2.9. Conclusion

Globally, the importance of developing financial inclusion has been widely recognised by policy makers and scholars in recent years. Thanks to the development of data such as, for instance, the World Bank Global Findex Database and the IMF Financial Access Survey, a growing literature has been studying the measurement, determinants, and impact of financial inclusion worldwide. However, due to the heterogeneity in social and economic development among countries, it is necessary to look at financial inclusion in separate countries. Although China is the largest emerging economy, its financial inclusion profile has not been fully discussed in the literature. This study fills this gap by providing insights in the following aspects:

First, since informal financing plays a crucial role in the Chinese context, I investigate the links between informal financing and several measures of financial inclusion at the household level. To the best of my knowledge, this issue has not been investigated before. Second, I test, for the first time, the extent to which financial inclusion affects household consumption. Finally, this study is the first to remove “voluntary exclusions” from the sample used, which is likely to lead to more reliable results.

I use a representative household level dataset, the 2013 wave of the China Household Finance Survey, which covers more than 20,000 households from 29 provinces (municipalities) in China. Based on various specifications, I document that informal financing and financial inclusion are substitutes at the household level in China. Next, I document that financial inclusion is strongly associated with a higher level of household consumption. From a policy viewpoint, these findings suggest that the prevalence of informal finance among Chinese households may crowd out the need and usage of formal financial services. Policies aiming at improving accessibility to financial services may contribute to higher financial inclusion. In addition, promoting financial inclusion helps stimulate domestic consumption, which is a key policy objective in China.

2.10. Limitations and future research

There are several limitations in the present study. First, only associations, other than causal relationships, can be identified due to the cross-sectional structure of the data I use. Second, other covariates in the estimations such as income and net wealth are likely to be endogenous, especially in the regressions for household non-durable consumption. Thus, future research will focus on instrumenting the potentially endogenous household income/wealth once community level data or more waves of CHFS become available. Further research could also investigate the intensity of using financial services other than the coverage of these financial services.

Table 2. 1 Summary statistics and differences between urban and rural groups

Variable	Full Mean	Full S.D.	Urban Mean	Urban S.D.	Rural Mean	Rural S.D.	Diff
Dependent variables							
Account	0.635	0.482	0.723	0.448	0.445	0.497	0.277***
Credit	0.160	0.367	0.221	0.415	0.0296	0.170	0.192***
Floan	0.142	0.349	0.145	0.352	0.135	0.341	0.010**
Inclusion	0.696	0.460	0.774	0.418	0.527	0.499	0.247***
TotalC (RMB)	36,595	28,071	41,909	29,173	25,086	21,395	16,823***
Control variables							
Infloan	0.255	0.436	0.218	0.413	0.335	0.472	-0.117***
Age	51.43	14.38	50.35	14.98	53.74	12.68	-3.389***
Male	0.757	0.429	0.699	0.459	0.883	0.322	-0.184***
Illiterate	0.0790	0.270	0.0489	0.216	0.144	0.351	-0.095***
Secondaryedu	0.278	0.448	0.355	0.478	0.114	0.317	0.241***
Tertiaryedu	0.0869	0.282	0.126	0.332	0.00236	0.0485	0.124***
Married	0.858	0.349	0.845	0.362	0.887	0.317	-0.042***
Widowed	0.0694	0.254	0.0667	0.250	0.0753	0.264	-0.009***
Income (RMB)	46,291	76,363	56,671	85,471	24,040	44,114	32,631***
Netwealth (RMB)	537,645	809,372	709,537	906,162	170,781	321,017	538,759***
Hhsize	3.480	1.628	3.228	1.438	4.023	1.863	-0.795***
Homeowner	0.812	0.390	0.750	0.433	0.946	0.226	-0.196***
Job	0.674	0.469	0.603	0.489	0.826	0.379	-0.224***
Risk_averse	0.732	0.443	0.726	0.446	0.746	0.435	-0.020***
Grade	0.678	0.818	0.797	0.844	0.422	0.695	0.375***
Party	0.165	0.371	0.196	0.397	0.0989	0.299	0.097***
No. of obs.	28,060		19,146		8,914		

Notes: S.D. stands for standard deviation. All variables are dummies except for *TotalC, Age*, *income*, *netwealth*, *hhsize* and *Grade*. The Diff column presents the p-value of t-tests of the difference in each variable between the urban and rural groups. See Appendix 2.1 for complete definitions of all variables.

Table 2. 2 Marginal effects of determinants of financial inclusion

	Account			*Credit*			*Floan*			*Inclusion*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*full*	*urban*	*rural*	*full*	*urban*	*rural*	*full*	*urban*	*rural*	*full*	*urban*	*rural*
Infloan	-0.066***	-0.064***	-0.073***	-0.033***	-0.042***	-0.011**	0.082***	0.086***	0.079***	-0.028***	-0.042***	0.004
	(0.006)	(0.007)	(0.011)	(0.006)	(0.008)	(0.005)	(0.008)	(0.009)	(0.014)	(0.009)	(0.010)	(0.018)
Age	0.000	0.000	0.000	-0.004***	-0.006***	-0.001***	-0.004***	-0.006***	-0.001	-0.002***	-0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Male	0.001	0.003	-0.007	-0.023***	-0.033***	0.007	-0.023**	-0.015	-0.017	-0.034***	-0.020**	-0.054*
	(0.007)	(0.007)	(0.019)	(0.006)	(0.008)	(0.010)	(0.009)	(0.010)	(0.026)	(0.011)	(0.010)	(0.031)
Illiterate	-0.117***	-0.108***	-0.136***	-0.026	-0.068**	0.003	-0.031	-0.020	-0.065***	-0.064***	-0.045**	-0.107***
	(0.011)	(0.014)	(0.017)	(0.018)	(0.028)	(0.010)	(0.019)	(0.031)	(0.025)	(0.015)	(0.019)	(0.028)
Secondary	0.071***	0.072***	0.043***	0.101***	0.140***	0.004	0.039***	0.029***	0.038*	0.095***	0.082***	0.073**
	(0.007)	(0.007)	(0.017)	(0.006)	(0.008)	(0.007)	(0.009)	(0.010)	(0.021)	(0.010)	(0.010)	(0.030)
Tertiary	0.125***	0.119***	0.122	0.184***	0.241***	0.059*	0.086***	0.065***	-0.105	0.182***	0.152***	-0.016
	(0.013)	(0.012)	(0.103)	(0.008)	(0.011)	(0.033)	(0.013)	(0.013)	(0.123)	(0.022)	(0.019)	(0.152)
Married	0.027**	0.026**	0.032	0.029***	0.041***	0.005	0.060***	0.048***	0.136***	0.008	0.010	0.028
	(0.012)	(0.012)	(0.029)	(0.010)	(0.013)	(0.015)	(0.015)	(0.017)	(0.041)	(0.016)	(0.016)	(0.044)
Widowed	0.005	0.005	0.005	0.038**	0.067***	-0.014	0.046*	0.059**	0.085	-0.021	0.007	-0.069
	(0.016)	(0.017)	(0.036)	(0.017)	(0.024)	(0.023)	(0.024)	(0.029)	(0.052)	(0.022)	(0.023)	(0.055)
Lincome	0.018***	0.016***	0.026***	0.004***	0.004***	0.002	0.008***	0.006***	0.014***	0.014***	0.012***	0.024***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.001)	(0.004)
Lwealth	0.061***	0.056***	0.073***	0.052***	0.067***	0.018***	0.069***	0.088***	0.033***	0.048***	0.041***	0.068***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.005)	(0.002)	(0.002)	(0.006)
Hhsize	-0.010***	-0.011***	-0.010***	0.006***	0.008***	0.003**	0.009***	0.007**	0.012***	-0.007***	-0.010***	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)
Homeowner	-0.114***	-0.113***	-0.087***	-0.058***	-0.076***	-0.022*						
	(0.009)	(0.009)	(0.026)	(0.007)	(0.010)	(0.012)						
Job	-0.018**	-0.022***	-0.003	0.038***	0.054***	-0.009	0.030***	0.012	0.040*	0.002	-0.008	0.022
	(0.007)	(0.008)	(0.016)	(0.007)	(0.010)	(0.008)	(0.010)	(0.012)	(0.021)	(0.011)	(0.011)	(0.025)

Risk_averse	0.008	0.012*	0.003	-0.022***	-0.034***	0.002	-0.022***	-0.018**	-0.021	0.004	0.010	-0.010
	(0.006)	(0.007)	(0.012)	(0.005)	(0.008)	(0.005)	(0.008)	(0.009)	(0.015)	(0.009)	(0.009)	(0.020)
Grade	0.048***	0.045***	0.048***	0.037***	0.045***	0.018***	0.012***	0.007	0.025***	0.056***	0.048***	0.068***
	(0.004)	(0.004)	(0.008)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.009)	(0.006)	(0.006)	(0.013)
Party	0.049***	0.055***	0.026	0.027***	0.031***	0.020***	0.005	-0.009	0.090***	0.060***	0.050***	0.080***
	(0.008)	(0.009)	(0.018)	(0.007)	(0.009)	(0.007)	(0.010)	(0.011)	(0.022)	(0.013)	(0.013)	(0.030)
Rural	-0.033***			-0.093***			0.090***			-0.030***		
	(0.007)			(0.008)			(0.010)			(0.010)		
Observation	25,402	17,670	7,732	18,026	12,311	5,715	12,998	9,344	3,654	9,613	6,807	2,806

Notes: Income and net wealth are in logarithm. All regressions were estimated using a Probit model. Dependent variables are *Account*, *Credit*, *Floan* and *Inclusion*, respectively. Voluntary exclusions are removed from all estimations. Provincial dummies are included in all regressions. Robust standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Appendix 2.1 for complete definitions of all variables. *Homeowner* is excluded from the *Floan* and *Inclusion* regressions as mortgage is the main component of *Floan*.

Table 2. 3 Financial inclusion and household consumption

	(1)	(2)	(3)	(4)	(5)	(6)
	full	*full*	*rural*	*rural*	*urban*	*urban*
Account	0.123***		0.099***		0.131***	
	(0.009)		(0.016)		(0.010)	
Credit	0.241***		0.294***		0.254***	
	(0.010)		(0.042)		(0.011)	
Floan	0.086***		0.132***		0.078***	
	(0.011)		(0.024)		(0.012)	
Inclusion		0.155***		0.123***		0.173***
		(0.009)		(0.016)		(0.012)
Age	-0.008***	-0.009***	-0.014***	-0.014***	-0.005***	-0.006***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Male	-0.039***	-0.045***	-0.043	-0.041	-0.042***	-0.049***
	(0.009)	(0.009)	(0.026)	(0.026)	(0.010)	(0.010)
illiterate	-0.111***	-0.096***	-0.034	-0.032	-0.161***	-0.142***
	(0.018)	(0.018)	(0.026)	(0.026)	(0.025)	(0.025)
Secondaryedu	0.112***	0.137***	0.108***	0.110***	0.118***	0.146***
	(0.009)	(0.009)	(0.024)	(0.024)	(0.010)	(0.010)
Tertiaryedu	0.169***	0.253***	0.046	0.083	0.195***	0.276***
	(0.014)	(0.014)	(0.137)	(0.131)	(0.015)	(0.015)
Married	0.187***	0.194***	0.228***	0.231***	0.167***	0.177***
	(0.016)	(0.016)	(0.040)	(0.040)	(0.017)	(0.017)
Widowed	0.052**	0.064***	0.166***	0.169***	-0.005	0.015
	(0.023)	(0.023)	(0.050)	(0.050)	(0.026)	(0.026)
Lincome	0.027***	0.028***	0.051***	0.052***	0.019***	0.020***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
Lwealth	0.128***	0.135***	0.109***	0.112***	0.134***	0.143***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
Hhsize	0.102***	0.101***	0.106***	0.108***	0.096***	0.096***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Homeowner	-0.193***	-0.202***	-0.169***	-0.173***	-0.218***	-0.229***
	(0.011)	(0.012)	(0.037)	(0.037)	(0.012)	(0.012)
Job	-0.104***	-0.091***	-0.065***	-0.068***	-0.076***	-0.063***
	(0.010)	(0.010)	(0.022)	(0.022)	(0.011)	(0.011)
Risk_averse	-0.044***	-0.050***	-0.058***	-0.059***	-0.039***	-0.048***
	(0.008)	(0.008)	(0.017)	(0.017)	(0.009)	(0.009)
Grade	0.055***	0.063***	0.079***	0.084***	0.046***	0.056***
	(0.005)	(0.005)	(0.011)	(0.011)	(0.005)	(0.005)
Party	0.067***	0.072***	0.067***	0.077***	0.054***	0.060***
	(0.010)	(0.010)	(0.026)	(0.026)	(0.011)	(0.011)
Rural	-0.203***	-0.211***				
	(0.011)	(0.011)				
Constant	8.581***	8.553***	8.642***	8.635***	8.457***	8.399***
	(0.047)	(0.047)	(0.101)	(0.102)	(0.052)	(0.053)
Observations	25,014	25,026	7,559	7,560	17,455	17,466
R-squared	0.463	0.452	0.374	0.369	0.415	0.397

Notes: Household total non-durable consumption, income and net wealth are in logarithm. All regressions are estimated using OLS. Provincial dummies are included in all regressions. Robust standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Appendix 2.1 for complete definitions of all variables.

Table 2. 4 Marginal effects of *Infloan* using *Sibling_dum* as IV

Panel A Full sample	**Special regressor**			
	Account	*Credit*	*Floan*	*Inclusion*
ME of I*nfloan*	-0.534***	-0.346**	-0.211**	-0.256**
S.E.	0.077	0.162	0.107	0.105
No. of observations	24,148	17,137	12,358	9,139
	Bivariate probit			
	Account	*Credit*	*Floan*	*Inclusion*
ME of I*nfloan*	-0.270***	-0.269***	-0.120***	-0.155***
S.E.	0.067	0.014	0.040	0.058
No. of observations	25,402	18,026	12,998	9,613
Panel B Rural sample	**Special regressor**			
	Account	*Credit*	*Floan*	*Inclusion*
ME of I*nfloan*	0.439	-0.014	-0.264	-0.374
S.E.	0.375	0.041	0.273	0.325
No. of observations	7,351	5,434	3,474	2,668
	Bivariate probit			
	Account	*Credit*	*Floan*	*Inclusion*
ME of I*nfloan*	-0.287***	-0.175***	-0.110***	-0.196***
S.E.	0.067	0.013	0.040	0.072
No. of observations	7,732	5,715	3,654	2,806
Panel C Urban sample	**Special regressor**			
	Account	*Credit*	*Floan*	*Inclusion*
ME of I*nfloan*	-0.424***	-0.554***	-0.320***	-0.256***
S.E.	0.070	0.101	0.145	0.080
No. of observations	16,799	11,704	8,884	6,472
	Bivariate probit			
	Account	*Credit*	*Floan*	*Inclusion*
ME of I*nfloan*	-0.262***	-0.310***	-0.125***	-0.137***
S.E.	0.068	0.015	0.040	0.052
No. of observations	17,670	12,311	9,344	6,807

Notes: Dependent variables are *Account*, *Credit*, *Floan*, and *Inclusion* respectively. The endogenous variable *Infloan* is instrumented using *Sibling_dum*. Other control variables are *Age*, *Male*, *Illiterate*, *Secondaryedu*, *Tertiaryedu*, *Married*, *Widowed*, (log of) *Income*, (log of) *Netwealth*, *Hhsize*, *Homeowner*, *Job*, *Risk*_averse, *Grade* and *Party*. ME denotes the marginal effect. Standard errors (S.E.) are obtained from 200 bootstrap samplings for both models. The marginal effects of other controls are not reported for brevity. The special regressor method is implemented by the STATA user written command *sspecialreg*. Voluntary exclusions are not included in the *Credit*, *Floan* and *Inclusion* regressions. In the bivariate probit setting, the marginal effect of *Infloan* is computed for urban and rural subsamples separately after estimating each bivariate probit model for the full sample. In the special regressor setting, the marginal effect of *Infloan* for urban and rural subsamples are obtained from separate regressions for urban and rural subsamples respectively.

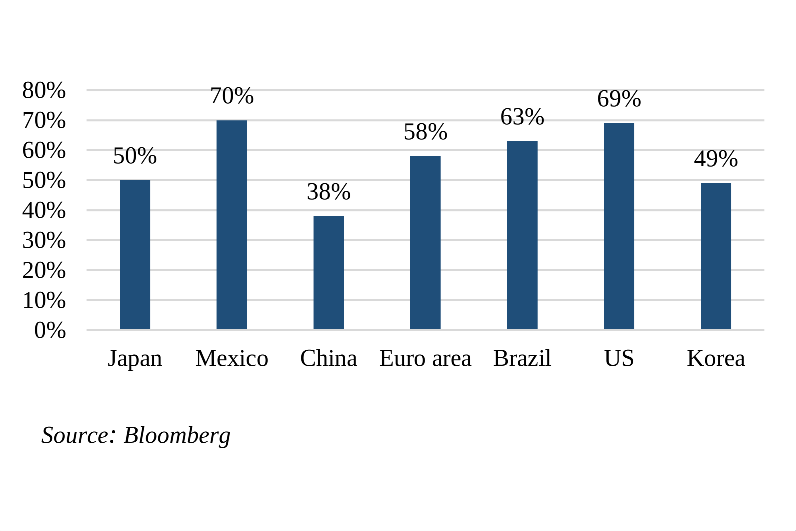

Figure 2. 1 Private Consumption as % GDP (2013)

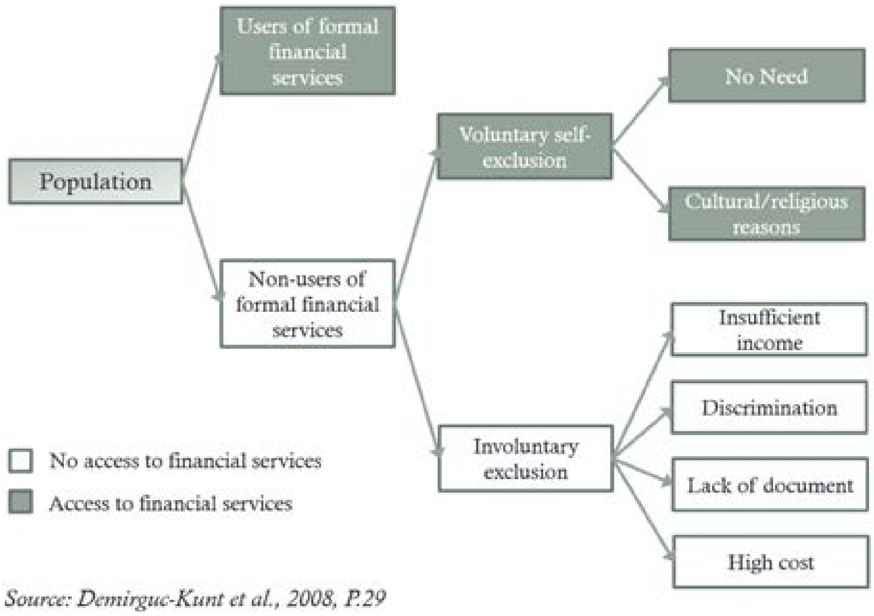

Figure 2. 2 Distinguishing Voluntary *vs*. Involuntary Exclusion

Appendix 2.1 Definitions of the variables used

Dependent variables	
Account	Dummy variable equal to 1 if the household has either a current account or a deposit account in a formal financial institution, and 0 otherwise
Credit	Dummy variable equal to 1 if the household has a credit card, and 0 otherwise
Floan	Dummy variable equal to 1 if the household currently has formal loans from banks, and 0 otherwise
Inclusion	Dummy variable equal to 1 if the household currently has either a bank account, and/or a credit card, and/or a bank loan, and 0 otherwise
TotalC	Continuous variable: household total non-durable consumption (yearly)
Independent variables	
Infloan	Dummy variable equal to 1 if the household has loans from informal sources, and 0 otherwise
Age	Discrete variable: Household head's age measured in year
Male	Dummy variable equal to 1 if the household head is male, and 0 if female
Illiterate	Dummy variable equal to 1 if the household head is illiterate, and 0 otherwise
Secondaryedu	Dummy variable equal to 1 if the household head has completed secondary education, and 0 otherwise
Tertiaryedu	Dummy variable equal to 1 if the household head has completed tertiary education or above, and 0 otherwise
Married	Dummy variable equal to 1 if the household head is married, and 0 otherwise
Widowed	Dummy variable equal to 1 if the household head is widowed, and 0 otherwise
Income (RMB)	Continuous variable: household total income (yearly)
Netwealth (RMB)	Continuous variable: household total wealth minus total debts (yearly)
Hhsize	Discrete variable: number of household members
Homeowner	Dummy variable equal to 1 if the household head is a home-owner, and 0 otherwise
Job	Dummy variable equal to 1 if the household head is currently working, and 0 otherwise
Risk_averse	Dummy variable equal to 1 if the household head is risk averse, and 0 otherwise
Grade	Discrete variable: [0,3] indicating household head's financial literacy; 0 represents the lowest financial literacy and 3 represents the highest financial literacy
Party	Dummy variable equal to 1 if the household head is a communist party member, and 0 otherwise
Rural	Dummy variable equal to 1 if the household resides in rural areas, and 0 otherwise
Sibling_dum	Dummy variable equal to 1 if the household head or his/her spouse has siblings, and 0 otherwise

Source: 2013 wave of the CHFS

Appendix 2.2 Further investigations of the characteristics of voluntary exclusions

Appendix Table 2.2a presents descriptive statistics for samples with and without voluntary exclusions. We can see that the sample means of the four financial inclusion indicators are significantly different between the groups with and without voluntary exclusions. Specifically, the full sample without voluntary exclusions has a much higher level of *Credit* and a much higher level of *Floan*, a slightly higher level of *Inclusion*, and a lower level of *Account*. This is because observations who like spending cash and/or do not need bank loans are removed from the sample. Omitting exclusions also leads to a higher average total consumption. Next, I investigate the determinants of the voluntary exclusions. I thus perform Probit estimations identical to Equation 2.1 whereby the dependent variable is given by the voluntary exclusions. Marginal effects of these Probit estimations are reported in Table 2.2b.

We can see that, households with older heads are more likely to like spending cash and do not need bank loans. Households with higher income and/or net wealth are more likely to become voluntarily excluded, which reflects a lower need for financial services among richer households. Being risk averse is positively associated with the likelihood of having a preference on spending cash but does not seem to be closely related to a lack of need for formal loans. Homeownership is strongly positively correlated with type II exclusions. This is not surprising as the main component of formal loans in my sample is made up by mortgages and households who already own a home are less like to demand mortgages compared to renters. Being a party member is strongly associated with a lower probability of having no need for bank loans. Residing in rural areas is significantly associated with a lower probability of having a preference on spending cash and a high probability of lack of need for bank loans. This may be caused by the fact that the percentage of home owners is higher among rural households than urban households.

Appendix Table 2.2a Means and standard deviations for samples with and without voluntary exclusions

	Full sample (N=28,060)		Full sample without voluntary exclusions (N=10,868)		Type I Exclusion: Like spending cash (N=7,956)		Type II Exclusion: No need for bank loans (N=13,545)	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Account	0.635	0.482	0.617	0.486	0.665	0.472	0.643	0.479
Credit	0.160	0.367	0.259	0.438	-	-	0.125	0.330
Floan	0.142	0.349	0.284	0.451	0.112	0.316	-	-
Inclusion	0.696	0.460	0.729	0.445	0.702	0.457	0.658	0.475
TotalC	36595	28071	38746	30682	35701	24438	34824	26443
Infloan	0.255	0.436	0.309	0.462	0.231	0.422	0.205	0.404
Age	51.43	14.38	49.40	14.17	52.45	14.16	53.21	14.44
Male	0.757	0.429	0.754	0.431	0.762	0.426	0.759	0.428
Illiterate	0.0790	0.270	0.0761	0.265	0.0618	0.241	0.0891	0.285
Secondary	0.278	0.448	0.284	0.451	0.298	0.457	0.266	0.442
Tertiary	0.0869	0.282	0.116	0.321	0.0598	0.237	0.0674	0.251
Married	0.858	0.349	0.851	0.356	0.875	0.331	0.859	0.348
Widowed	0.0694	0.254	0.0651	0.247	0.0675	0.251	0.0760	0.265
Income	46291	76363	46770	76313	44803	72564	46807	78586
Netwealth	537645	809372	524756	846416	530941	745407	561071	798101
Hhsize	3.480	1.628	3.515	1.628	3.438	1.586	3.457	1.640
Homeowner	0.812	0.390	0.755	0.430	0.823	0.382	0.873	0.333
Job	0.674	0.469	0.705	0.456	0.641	0.480	0.654	0.476
Risk averse	0.732	0.443	0.719	0.449	0.744	0.436	0.741	0.438
Grade	0.678	0.818	0.716	0.841	0.692	0.806	0.633	0.797
Party	0.165	0.371	0.167	0.373	0.169	0.375	0.161	0.368
Rural	0.318	0.466	0.309	0.462	0.280	0.449	0.340	0.474

Source: 2013 China Household Finance Survey. See Appendix 2.1 for detailed definitions of all variables.

Appendix Table 2.2b Probit regressions for voluntary exclusions

	Type I: like spending cash (1)	Type II: do not need loans (2)
Age	0.001***	0.004***
	(0.000)	(0.000)
Male	0.010	-0.015*
	(0.007)	(0.008)
Illiterate	-0.071***	0.014
	(0.012)	(0.013)
Secondaryedu	-0.017**	-0.042***
	(0.007)	(0.008)
Tertiaryedu	-0.123***	-0.118***
	(0.012)	(0.013)
Married	0.044***	-0.059***
	(0.012)	(0.013)
Widowed	0.031*	-0.083***
	(0.017)	(0.018)
Lincome	0.003***	0.007***
	(0.001)	(0.001)
Lwealth	0.009***	0.036***
	(0.002)	(0.002)
Hhsize	-0.005**	-0.012***
	(0.002)	(0.002)
Homeowner	0.005	0.110***
	(0.009)	(0.010)
Job	-0.020***	0.002
	(0.008)	(0.008)
Risk_averse	0.011*	0.002
	(0.006)	(0.007)
Grade	0.005	-0.021***
	(0.004)	(0.004)
Party	-0.003	-0.029***
	(0.008)	(0.009)
Rural	-0.039***	0.055***
	(0.008)	(0.008)
Observations	25,440	25,440

Notes: Income and net wealth are in logarithm. All regressions were estimated using a probit model. Dependent variables are type I and II voluntary exclusions respectively. Provincial dummies are included in all regressions, but the marginal effects of provincial dummies are not reported for brevity. Robust standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Appendix 2.1 for complete definitions of all variables.

Chapter Three: To What Extent Does Household Consumption Respond to Health Shocks? Evidence from the China Health and Retirement Longitudinal Study

3.1. Introduction

According to the Life-Cycle Hypothesis (LCH) proposed by Modigliani and Brumberg (1954) and the Permanent Income Hypothesis (PIH) of consumption proposed by Friedman (1957), consumption is determined by the value of lifetime resources or, in the latter case, by one's permanent income defined as expected income in future years. If the expected income equals to the annuity value of lifetime resources, the two theories are very close (Deaton, 1992)[14]. It is predicted that agents' consumption only responds to changes in permanent income and should not respond to anticipated and/or transitory income changes. Consequently, any shock that can potentially lead to fundamental changes of agents' expected income may have great impact on their consumption choices.

Acute health shocks, among others, are examples of permanent shocks which can largely affect individuals' consumption decisions. Health shocks can affect consumption through both direct and indirect channels. On one hand, the presence of health shocks limits individuals' working hours and productivity. Furthermore, if the shocks are persistent, individuals may partly or fully exit the labour market. Hence, the shocks have a direct impact on one's permanent income. On the other hand, health shocks increase out-of-pocket medical

[14] Although both theories predict consumption smoothing, the LCH pays more attention to the relationship between age and wealth accumulation/decumulation, while the PIH puts more emphasis on the dynamics of consumption in a relative shorter period. As the main concern of this paper is to investigate the fluctuations of consumption after health shocks, the PIH is the favoured theory in this context. Hence, in the remaining chapter, the PIH other than the LCH is mentioned.

expenditure on obtaining treatments and care, so that the consumption on other items is constrained and the overall consumption level might be affected consequently.

The extent of the sensitivity of consumption to health shocks depends on the persistence of the shocks and the degree of imperfection of credit and insurance markets. When health shocks occur, households can smooth their consumption if they own health insurance, have accumulated precautionary savings, and/or are able to borrow from formal and/or informal sources (Babiarz et al., 2012, Wagstaff, 2007). Ideally, if the markets are complete, households' idiosyncratic shocks will be mitigated by risk-sharing institutions, and household consumption changes over time should purely result from the growth of aggregate consumption (Gertler and Gruber, 2002). However, empirical studies have found evidence against the full insurance theory, although the extent of this failure varies (Gertler and Gruber, 2002, Babiarz and Yilmazer, 2017, Yilmazer and Scharff, 2014). For households living in low- and middle-income countries (LMICs) with inadequate insurance and credit markets, the costs of health adversities can be considerably high. Acute health shocks fundamentally change households' consumption decisions (Alam and Mahal, 2014), as they significantly increase out-of-pocket health expenditure (Saksena et al., 2010, Van Doorslaer et al., 2006, Wagstaff and Doorslaer, 2003), reduce hours worked and labour income (Gertler and Gruber, 2002, Lindelow and Wagstaff, 2005, Wagstaff, 2007), which lead, in turn, to declines in non-medical consumption (Asfaw and Braun, 2004, Gertler et al., 2009, Wagstaff and Lindelow, 2010) in LMICs. Moreover, to cope with the shocks, households are likely to take on unsecured debts (Babiarz et al., 2013), leading to further uncertainties in life.

Although health risk and its impact on agents' consumption profile have earned considerable attention among researchers and policy makers alike, under the background of global ageing, convincing empirical evidence for the older population on this topic is very limited. Compared to younger adults, elderly people are more prone and vulnerable to health shocks. Many diseases, such as arthritis, back and neck pain, heart problems and diabetes, have higher occurrences among older people (World Health Organization, 2018). Furthermore, as human capital decreases with age, elderly people have lower or no labour earnings compared to their younger counterparts. I therefore expect older people to act differently in the presence of a health shock.

China stands out as a special case for studying the impact of health shocks on consumption among older people for several reasons. First, China has the world's largest older population and the rate of population ageing is accelerating (Smith et al., 2014). According to the United Nations, due to declining fertility rates and rising life expectancy, by 2050, China will have more than 400 million people aged 65 and over, which accounts for more than one quarter of the total population in (United Nations, 2017). In 1950, the average number of children per women was 6, and the average life expectancy was only 45 years in China. However, in 2015, these two numbers were 1.5 and 75, respectively. Population ageing has profound impacts on a wide range of economic and social issues. Among them, economic burden and elderly care are two main challenges facing China (Smith et al., 2014). A better understanding of older people's consumption profile could potentially help assess the economic burden brought by health shocks and ultimately contribute to improvements in the healthcare system China.

Second, China's share of out-of-pocket (OOP) payment in total health expenditure, on average, is 35 percent despite the fact that a universal coverage scheme was achieved since 2011. This can be explained by, at the micro-level, inpatient care utilised by the insured is covered with an average reimbursement rate between 44 percent and 68 percent, depending on the insurance scheme (Zhang et al., 2017). However, the outpatient service usage is only covered in some counties. Under these circumstances, OOP medical expenditure will be expected to increase dramatically if one is experiencing a severe health shock. As elderly people face reduced labour earnings, large OOP medical expenditure is likely to erode their non-medical consumption and well-being.

Third, due to the underdevelopment of financial markets, individuals in China face significant financial constraints that impede borrowing from formal financial institutions[15]. When a health shock occurs and OOP medical expenditure increases, Chinese households tend to rely on dissaving and/or informal borrowing from family members, relatives or friends. Once dissaving and borrowing are not available in the absence of complete financial markets, high OOP medical expenditure may lead to impoverishment and even a vicious spiral of poverty and ill health (Li et al., 2014).

This chapter aims at investigating the extent to which both objectively and subjectively measured health shocks affect Chinese older people's consumption decisions. To the best of my knowledge, although the impact of health shocks has been widely discussed in the literature, only few studies have adopted both subjective and objective measures of health shocks, and only very few studies looked at elderly people in China. This study contributes to the existing literature in several ways. Firstly, it measures health shocks in two ways and includes an arguably more exogenous measure of health shocks – accidents as a robustness check to eliminate biases posed by the difference between self-reported and actual health status. Second,

[15] For more discussion about liquidity constraints and financial exclusions in China, please refer to Chapter 2 of this thesis.

this study specifically focuses on elderly people in China, the largest older population group worldwide, using a recent and representative dataset, the China Health and Retirement Longitudinal Study (CHARLS). Third, I differentiate my findings between subgroups of the population according to a range of regional and socioeconomic divisions considering wide disparities existing between urban and rural areas as well as across provinces in China. This study will provide insights on addressing the healthy ageing issue in China.

The remainder of this chapter is organised as follows. In Section 3.2, I provide a brief introduction to the background of the healthcare system in China. Section 3.3 summarises findings in the literature on the impacts of health shocks on consumption and on other outcomes affecting households' consumption. Section 3.4 develops the hypotheses. Data summary statistics and methodology are presented in Section 3.5 and 3.6, respectively. Section 3.7 presents the empirical results. In Section 3.8, I conduct several robustness tests. Section 3.9 concludes, and Section 3.10 discusses limitations of this study and future research directions.

3.2. Public health insurance system in China[16]

China has achieved a universal health insurance coverage since 2011. This process has been recognised as "unparalleled" (Liang and Langenbrunner, 2013). Although evaluating the effectiveness of China's health insurance schemes is not the main purpose of this chapter, an introduction to the background of the public health insurance system in China helps us understand why the OOP medical expenditure that Chinese households are facing is still high despite the full coverage provided by the public health insurance. As a result, a large number of people do not seek for healthcare due to high OOP medical costs and their inability to pay for such costs (Wang et al., 2018).

In China, health-related legislations and policies are designed by the central government. Yet, health insurance is directly provided and financed by local governments with local discretion. There are three types of health insurance schemes in China. Employees including retirees in urban areas are covered by the Urban Employee Basic Medical Insurance (UEBMI), whilst unemployed urban residents are eligible for self-enrolling in the Urban Resident Basic Medical Insurance (URBMI). Rural residents and some migrants can voluntarily participate in the New Rural Cooperative Medical Scheme (NRCMS). In addition, the Medical Assistance (MA) programme was launched in 2003 to provide supplementary medical funding to the extremely poor residents.

The premium of all schemes is largely affordable. The yearly enrolment fee is only 140 RMB (≈ 22 USD) for the URBMI and 160 RMB (≈ 25USD) for the NRCMS with the personal contribution being as low as 20 RMB (≈3 USD) for both schemes in 2010 (Zhang et al., 2017).

[16] This section largely draws on the People's Republic of China Health System Review (World Health Organization, 2015) and the International Healthcare System Profiles - China (Mossialos et al., 2017).

However, the share of total medical expenditure that can be financed by these public health insurance schemes is rather limited. Inpatient and outpatient services are financed differently, and deductibles, co-payments and ceilings are used by all three medical insurance schemes[17]. UEBMI is the most generous public insurance scheme which has the widest medical service coverage, highest reimbursement rates and ceilings compared to that of URBMI and NRCMS. Outpatient service utilisation is covered by the UEBMI nation-wide, but it is only covered by the URBMI and NRCMS in some developed counties.

The proportion of medical expenditure which can be covered by the public health insurance schemes differs not only across regions but also amongst the levels of healthcare providers. In China, health service providers are categorised into tertiary hospitals, secondary hospitals and primary healthcare centres. Tertiary hospitals are normally located in the most developed cities like Beijing, Shanghai and the capital city of each province. The best medical equipment and experts are concentrated in tertiary hospitals. Primary healthcare providers include community health centres, rural health units and stations. Compared to hospitals, they have limited capacities and can only deal with basic medical conditions. Secondary healthcare providers offer a wider range of services compared to that of primary provides, but the quality of their services are not as good as tertiary hospitals. Using the same medical service at different health institutions is subject to different reimbursement rates. Taking Shanghai as an example, in 2013, for city employees with the UEBMI, only 50 percent of outpatient service expenditure higher than the deductible (1500 RMB) could be reimbursed at the tertiary level, while 60

[17] For clear definitions of deductibles, co-payments and ceilings, please see (World Health Organization, 2015).

percent and 65 percent of the expense incurred at the secondary and primary level could be reimbursed, respectively[18].

In addition to the varying reimbursement rates, only limited medical services and medicines on the national insurance reimbursement list are eligible for reimbursement. For example, if a patient with public health insurance is treated with services and medicines outside of the national insurance list, s/he needs to pay for the full cost of using these medicines. Moreover, both home and hospice medical care expenditures are not covered in all public medical insurance schemes.

In 2016, the OOP health expenditure accounted for less than 30 percent of total health expenditure. This percentage was more than halved compared to that in 2001 (National Bureau of Statistics of China, 2017). Despite the great reduction in the share of OOP health expenditure brought by the universal coverage of public health insurance, Zhang et al. (2017) argue that the current health insurance system boosts regional inequalities because the healthcare resources are not distributed evenly across regions. In addition, although having public health insurance indeed reduces OOP medical expenditure, those with very high medical bills are still at risk due to the shallow coverage of these health insurance schemes.

In this context, Chinese individuals who are going through severe health shocks are vulnerable. Firstly, certain diseases can only be treated at tertiary hospitals and several specialised secondary hospitals, but the reimbursement rate at this level is lower than that at the primary level. Secondly, certain diseases often require treatments and medicines which are not on the national insurance list. Patients will have to pay 100 percent of these costs as OOP

[18] Source: The Shanghai Municipal Human Resources and Social Security Bureau, URL: http://www.12333sh.gov.cn/201712333/index.shtml [In Chinese]

expenses. Thirdly, since aftercare and preventive treatments are not generally covered in public health insurance schemes, post-shock individuals are likely to face high OOP medical bills for a long period of time. Thus, Individuals without enough savings or assets and lack of formal and informal access to credit may withdraw from treatments due to their inability to pay for the OOP medical costs. Alternatively, they may have to reduce essential consumption on other items in order to finance their rising OOP medical expenditure after a health shock.

3.3. Literature review

The relationship between health shocks and socio-economic outcomes in both low and middle income countries (LMICs) and other countries has been widely discussed in literature (Liu, 2016, Genoni, 2012, Mohanan, 2013, Nguyet and Mangyo, 2010, Wagstaff, 2007, Lindelow and Wagstaff, 2005). The scope of socio-economic outcomes is ranging from, but not limited to, earnings (Lindelow and Wagstaff, 2005, García-Gómez et al., 2013), consumption (Mohanan, 2013, Liu, 2016, Asfaw and Braun, 2004, Gertler et al., 2009), labour market participation and supply (Gertler and Gruber, 2002, Lindelow and Wagstaff, 2005), as well as households' coping strategies (Sparrow et al., 2013, Nguyen et al., 2012). However, as various measurements of health shocks and estimating strategies are adopted, the findings are mixed. The remainder of this section will review all major health shock measurements and summarise the findings on the economic impact of health shocks in recent empirical studies.

3.3.1. Review of health shock measures

The most widely used measures of health shocks include, among others, changes in individuals' self-assessed health status (Clark and Etilé, 2002, García-Gómez, 2011, Lindelow and Wagstaff, 2005, Sundmacher, 2012), increased physical limitations (Gertler and Gruber, 2002, Gertler et al., 2009), new diagnoses of severe health conditions (Jones et al., 2016), and occurrences of accidents or injuries (Mohanan, 2013, Pohl et al., 2013, Zucchelli et al., 2010).

A health shock is usually defined as a change from self-reported excellent or good health to poor health between two waves of a survey[19]. The idea behind this is that a large drop in

[19] Mainstream health surveys such as HRS, SHARE, ELSA and CHARLS adopt a 5-point scale of self-rated health status. Respondents are asked to rate their health status into one of the following five categories: excellent, very good, good, fair and poor.

health status over a relatively short period of time is very likely to be caused by a severe health adversity, which is assumed to be unanticipated and exogenous (Lindelow and Wagstaff, 2005). Also, by differencing between waves, possible unobservable time-invariant factors which also affect outcomes of interest are removed.

However, there is an increasing number of empirical evidence showing that the self-reported health status is subject to considerable measurement errors. Bound (1989) discusses the reasons why self-assessed health measures are usually biased. First, individuals' subjective judgments on health status are not entirely comparable. Individuals with identical physical health conditions may have completely different self-perceptions on their health status. Secondly, individuals may have various incentives to misreport their health status. For example, those who exit the labour market earlier than others may use poor health as a 'legitimate' excuse to justify their behaviour. In addition, financial incentives also contribute to misreported health status since individuals with poor health may receive social benefits or paid leaves. However, this case may not apply to developing countries where such benefits are not commonly available. This suggests that self-reported health status may be a better proxy for health shock in LMICs than in developed countries with comprehensive social welfare systems. However, the issue of lacking comparability across individuals remains as a concern because individual's self-perceived health status may be affected by factors such as education background, risk attitude, and mental health status other than the actual health status. This issue can be partially solved by utilising micro-level dataset with comprehensive information on respondents' characteristics such as socioeconomic status, education background, risk attitude, preferences and so on to control for observable individual heterogeneities as much as possible.

To eliminate the concerns about the inaccuracy of self-perceived health status, recent studies have considered measuring health shocks by the deteriorations of individuals' mobility (Gertler and Gruber, 2002, Gertler et al., 2009). The activity of daily living score is an index measuring individuals' limitations in conducting various activities of daily livings (ADLs) such as bathing, dressing, and walking short distances. The ADL score has been proven reliable and valid for measuring physical health (Gertler and Gruber, 2002). A health shock is normally defined as an increase in the number of physical limitations between two survey waves, with the magnitude of such an increase varying across different studies. The ADL score has been seen as a reliable health predictor of morbidity and mortality by Millán-Calenti et al. (2010) and is widely believed to be more objective compared to the self-reported health status. Yet, the availability of ADL information is limited as not all surveys contain this information, and it is usually restricted to elderly individuals in surveys. In addition, individuals still have incentives to misreport their actual physical limitations for the reasons discussed above.

Other studies measure health shocks as the occurrence of new severe health conditions such as cancer, stroke, or heart problems. Although the information used is still self-reported by individuals, the probability of misreporting a health condition decreases with its severity (Baker et al., 2004). This suggests the incidence of new severe health conditions can be a fairly exogenous measure of health shocks. Furthermore, even though there is no reason to assume severe health conditions have no correlations with individuals' life style and socio-economic status, the occurrence of such conditions is very likely to be sudden and unpredictable (Jones et al., 2016).

Although the extent varies, it seems that all above-mentioned health shock measures based on individuals self-reported information are subject to measurement error and unobserved individual heterogeneity. However, self-reported health information is most convenient to collect, and the above-mentioned problems could be partially eliminated by applying appropriate econometric techniques such as differencing and/or propensity score matching, as well as controlling for a wide range of individual characteristics such as socioeconomic status, education backgrounds, risk attitude and preferences in regression analyses[20]. For above-mentioned reasons, these measures of health shocks remain one of the most widely used workhorses in the literature.

A strand of studies adopt more direct and objective measures of health shocks such as the occurrence of accidents or injuries (Mohanan, 2013, Pohl et al., 2013, Zucchelli et al., 2010), prolonged stays in hospital (García-Gómez et al., 2013, Schurer, 2014, Wagstaff, 2007)[21], a large drop in measured hand grip strength (Decker and Schmitz, 2016) or in measured body mass index (BMI) (Wagstaff, 2007)[22]. Compared to measures based on self-reported information, these measures are more objective and contain less reporting errors.

Mohanan (2013) uses the injuries sustained in bus accidents in India and matches passengers who were injured with passengers travelling on the same bus route but not injured. In this setting, the bus accident can be regarded as a random shock which is exogenous to individuals' personal characteristics. This enables casual effect inference on the possible impact of a shock on household consumption. Pohl et al. (2013) test the effect of health shocks on employment using administrative employment data combined with hospital records from Chile. They use traffic accidents as well as other external health shocks including injuries due to

[20] I will discuss the estimation strategies in depth in the methodology section.
[21] Data on the occurrence of accidents and length of hospitalisation are usually taken from local administrative databases.
[22] Measured hand grip strength, height and weight information is used here because self-reported hand grip strength, height/weight information is also subject to reporting errors.

falling, assault or fire as proxies of health shocks. This potentially solves the endogeneity issue of health shocks. Additionally, in contrast to other studies which mostly use survey data, this study takes advantage of the administrative data and provides new evidence on the effect of health shocks from an administrative aspect.

García-Gómez et al. (2013) define a health shock as a prolonged hospitalisation and investigate the causal effects of such a shock on employment and income in the Netherlands. They identify health shocks as unscheduled and urgent hospital admissions of individuals aged between 18 and 64 who have not been admitted in the previous year. Their measure of health shocks is more likely to be exogenous than self-reported measures. In addition, the prolonged admissions include not only external causes of injury such as road accidents, but also severe diseases of the circulatory and digestive system, poisoning and other injuries. Hence, it covers a far wider range of conditions than those caused by traffic accidents.

Similar to García-Gómez et al. (2013), Schurer (2014) exploits healthcare utilisation data for Germany and defines lengthy hospital stays or having more frequent doctor visits as health shocks[23]. Similarly, Wagstaff (2007) defines those who have been hospitalized during the past 12 months for seven days or more as individuals with health shocks.

Decker and Schmitz (2016) define health shocks by large drops of hand grip strength between two survey waves. The rationale of this measure is that poor muscle strength can be an objective sign of general health deterioration. The hand grip strength has been proven closely related to overall muscular strength, onset of severe chronic diseases and mortality (Rantanen et al., 2003, Roberts et al., 2011). Although the loss of hand grip strength is presumably a valid

[23] An individual is considered as suffering from a heath shock if he/she experiences an increase in the total number of healthcare visits/stays between two survey waves greater than one standard deviation in the sample.

measure of health shocks, this information is not universally available or/and is only available for limited waves in health-related surveys. As measuring hand grip strength requires the presence of a nurse or well-trained practitioner in addition to the interviewer, the cost of conducting this measure is higher than that of a normal interview.

Wagstaff (2007) measures health shocks as a sharp reduction of BMI. A sharp drop is defined as a drop exceeding one standard deviation of the distribution of BMI change between survey waves[24]. The author argues that BMI reduction is a good proxy for a health shock because a very low BMI (below 18.5) has been proven associated with an increasing risk of death. However, as the drop of BMI can be a result of healthier diets or more exercises other than severe and unanticipated health events, it remains unclear if BMI reduction should be used as an indicator for health shocks.

In a nutshell, there is a rigorous trade-off when choosing between measures of health shocks based on self-reported information and others. Self-reported measures may be subject to measurement errors and endogeneity issues, but objective measures are not flawless and more difficult to obtain. Strauss and Thomas (1998) argue that health is multidimensional and is usually measured with large errors. One health indicator alone is not adequate to capture all dimensions of health. Thus, multiple health indicators should be used. Therefore, in this study, I measure households' health shocks in two ways, namely the onset of severe condition(s) and deterioration of activities of daily living. Besides, I also use the occurrence of an accident, the most exogenous health shock measure, to conduct a set of robustness tests.

[24] This criterion does not vary across gender and age groups.

3.3.2. Wide impacts of health shocks

Health shocks have been found to be associated with reduced labour participation (Riphahn, 1999, Hagan et al., 2008, Danø, 2005, Disney et al., 2006), income loss (Gertler and Gruber, 2002, Lindelow and Wagstaff, 2005, Liu, 2016, Wagstaff, 2007), higher OOP medical expenditure (Nguyet and Mangyo, 2010, Mohanan, 2013) and reduced consumption on non-medical items (Gertler and Gruber, 2002, Saksena et al., 2010, Van Doorslaer et al., 2006, Wagstaff and Doorslaer, 2003, Kumara and Samaratunge, 2017, Wang et al., 2006)[25]. Empirical evidence for a non-significant change of food/non-medical expenditure is also plentiful (Nguyet and Mangyo, 2010, Genoni, 2012, Islam and Maitra, 2012, Fang et al., 2012, Mohanan, 2013, Liu, 2016, Mitra et al., 2016). However, in studies which find such non-significant impact of health shocks in the full sample, health shocks sometimes affect certain subgroups of the population. For example, Genoni (2012) finds evidence for a negative impact of health shocks on non-medical consumption for low-educated individuals, Nguyet and Mangyo (2010) find similar evidence for farm households. Mitra et al. (2016) find that households with female heads are least able to protect consumption against health shocks. The details of these studies are summarised as follows.

Taking a sample consisting of 19,509 full-time employed West-German and foreign individuals aged 40 to 59 from the first eleven waves (1984-1994) of the German Socio-Economic Panel, Riphahn (1999) finds that a health shock increases the probability of leaving the labour force and almost doubles the unemployment risk. In addition, health shocks have a

[25] As declined labour participation and earnings may adversely affect household's consumption profile by reducing available sources for consumption, I also include several studies investigating the impact of health shocks on labour outcomes in the present literature review.

larger impact on women than on men. Although the state welfare helps mitigate the negative impact of health shocks for the poorest section of the population, the mitigation is insufficient.

Using the European Community Household Panel (ECHP) over the period 1994-2001, Hagan et al. (2008) test the effect of health shocks across nine European Union counties and find evidence of an increasing probability of retiring following a health shock. Using a longitudinal sample from Denmark for the years 1981-2000, Danø (2005) finds that a road accident has a significantly negative impact on individuals' employment rates in both the short- and long-run, but no significant effect on disposable income. The result shows that Danish individuals' disposable income is well insured after a road injury. Using the British Household Panel Survey (1991-1998), Disney et al. (2006) find that current adverse health shocks reduce individuals' labour participations and that this effect is persistent among workers aged between 50 and the state pension age. Using a more recent survey, the UK Household Longitudinal Study (UKHLS), over the period 2009-2015, Jones et al. (2016) find that an acute health shock leads to a 7.2 percent reduction in labour market participation and doubles the risk of leaving the labour market (2009-2015). Using the ECHP for the years 1994-2001, García Gómez and López Nicolás (2006) find that health shocks reduce the probability of remaining in full time employment by 5.0 percent and increase the probability of becoming labour inactive by 3.5 percent in Spain. They also provide evidence that health shocks lead to potential spill-over effects on other household members' labour decisions.

Although the number of existing studies is limited, the empirical findings from LMICs also support the negative relationship between health shocks and labour related outcomes. Drawing data from the 1991 and 1993 Indonesian Resource Mobilization Study, Gertler and Gruber (2002) find that a health shock which is defined as a drop in the ADL index, leads to a

84 percent reduction in hours worked and a 74 percent increase in the probability of leaving the labour market in Indonesia.

3.3.3. Impact of health shocks on consumption

The empirical evidence on the effects of health shocks on consumption is mixed but abundant[26]. The results highly depend on countries, health shock measures used, as well as definitions of consumption.

As LMICs are characterised by incomplete financial markets, less generous public health insurance schemes and limited social safety nets, consumption smoothing in the presence of shocks might be more difficult for households in these countries. However, empirical results suggest that households' food consumption is well insured against health shocks in general, but the findings for non-food consumption are mixed. A large increase in OOP medical expenditure is consistently found following health shocks, with magnitude between 0 and 30 percent depending on the measures of shocks and on countries (Alam and Mahal, 2014).

Taking a sample from the 1993, 1997, and 2000 Indonesia Family Life Survey, Nguyet and Mangyo (2010) find that a health shock can result in a yearly reduction of work hours by up to 100 hours. In their study, the health shock is defined as a change of ADLs between two consecutive surveys. However, they find that non-medical consumption does not largely respond to health shocks. A one standard error adverse change of ADLs is associated with only a 1-3 percent change in food consumption.

[26] Here, I only review evidence obtained in the context of LMICs because LMICs are very distinctive from developed countries in terms of generosity of public health insurance schemes as well as development of credit and insurance markets.

Asfaw and Braun (2004) test the effect of health shocks on consumption in rural Ethiopia using data taken from the 1994 and 1995 Ethiopian Rural Household Surveys. The results suggest that while households' food consumption is insured against health shocks, their non-food consumption (medical expenditure excluded) declines significantly when the health status of a household's head changes from healthy to unhealthy. This finding suggests that neither households themselves nor existing risk-sharing arrangements in Ethiopia are sufficient to smooth households' non-food consumption against health shocks.

Similarly, Kumara and Samaratunge (2017) find that food consumption, as well as consumption on housing, clothing and other non-basic items, are not insured in Sri Lanka in the presence of adverse health events. They reach this conclusion using a sample of 20,535 households who were interviewed in the 2012/2013 Sri Lanka Household Income and Expenditure Survey. With the OOP medical expenditure increasing due to illnesses, poorer households are more likely to sacrifice food consumption as well as housing and clothing expenditures compared to the richer. However, non-basic consumption is still negatively affected for the rich, as they also need to finance the increasing OOP medical expenditure.

In contrast, Genoni (2012) finds no statistically significant evidence of health shocks defined as deterioration of physical functioning on household's total non-medical and food expenditure in Indonesia. Consumption seems fairly smooth following an adverse health event despite household earnings being significantly reduced after the shock. This finding contrasts those of Gertler and Gruber (2002), according to which, in the same country, using a similar health shock measure, deterioration of physical functioning compromises household non-medical consumption. Genoni (2012) explains that the difference between her findings and that of Gertler and Gruber (2002) is due to different assumptions about reverse causality and omitted bias. To be specific, Genoni (2012) uses an IV approach to address possible endogeneity of one's health status, but Gertler and Gruber (2002) assume exogeneity of their health shock measures and use an IV approach to instrument household's income change only.

In a quasi-experimental setting of bus accidents in India, Mohanan (2013) matches individuals involved in bus accidents with those who travelled on the same bus route but were not involved in accidents, and estimates the differences in consumption items between these two groups. He finds that health shock defined as exposure to bus accidents does not affect household's food, housing and festival consumption. Annual health spending among those suffering from a health shock is significantly higher than that of those who without. Education spending declines following the bus accident, but the magnitude of such reduction is small (548 Indian Rupees). The author further tests the possible mechanism that helps smooth consumption. He finds that the likelihood of households having debt or borrowing is around five times higher for households with a health shock compared to that of households without. This finding suggests that households exposed to a health shock finance their increasing health expenditure mainly through borrowing rather than reducing consumption on non-medical items.

Using a balanced panel consisting of 2,694 households in Bangladesh who participated in a longitudinal household level survey from 1997 to 2005, Islam and Maitra (2012) measure health shocks in multiple ways. They define three short-term health shock indicators, namely having any household member being sick during the last 15 days prior to the survey, the number of days of being sick and the number of days of refraining from work due to sickness; two long-term ones, namely having any big medical expenditure in the past year and death of main earner in the family. They do not find a significant association between household non-medical consumption and any measure of health shocks. They also point out that household's ability of insuring their consumption in the presence of a health shocks comes from selling livestock and/or other assets. Households with access to microcredit are less likely to sell assets compared to those without, following a health shock. This is because those who have access to microcredit could take loans when the income is affected after health shocks, and this avoids them from having to sell assets.

Mitra et al. (2016) also find a non-significant effect of health shocks on Vietnamese household's non-medical consumption. Specifically, they use data from 3 waves of the Vietnam Household Living Standards Survey covering the years 2004, 2006 and 2008. They find that health shocks are not significantly associated with household's total expenditure and non-food expenditure. The association between one health shock indicator (defined as days in which the respondent was unable to carry out regular activities) and food consumption is found to be statistically significant and negative, but the magnitude of such association is low. The authors also document that the medical expenditure increases largely after health shocks.

In the context of China, Liu (2016) assesses the role of public health insurance in mitigating the adverse outcomes resulting from health shocks in rural areas. Using the introduction of a large-scale health insurance scheme in rural China as a natural experiment and data taken from the China Household Nutrition Survey (CHNS), he finds that households' food consumption was fully insured against negative health shocks even before they were covered by the New Cooperative Medical Scheme (NCMS). However, a 10 percent increase in the size of a health shock was found associated with an 8 percent increase in child employment. Households with NCMS were less likely to reduce their children's education compared to those without NCMS following health shocks. This finding suggests that the health insurance (NCMS) seems to relieve the financial burden for households in illness and thus smooth their consumption. However, as the author only defines the health shock as the change of households' self-reported health status and the sample is limited to rural China, his results may be subject to endogeneity issues as well as sample selection bias.

Also using the CHNS, Lindelow and Wagstaff (2005) investigate the impact of health shocks on income, labour supply, consumption as well as medical expenditure in China. In their study, health shocks are defined as a large drop in the individual's self-assessed health status. They use fixed-effect models to address the unobserved individual heterogeneity of preferences or health endowments. They find that adverse health shocks are associated with substantial declines in income and labour supply and with a significant increase in OOP medical expenditure. The association is smaller, but still significant, for the poor. They also find that the increase in OOP medical expenditure is larger for those who have health insurance. This indicates that those who do not have health insurances are less likely to use healthcare services. The authors do not estimate the impact of health shocks on non-medical expenditure items.

Fang et al. (2012) study the impact of ill conditions on OOP medical expenditure as well as on other types of consumption in Western China. Their sample consists of three western cities, namely Lan Zhou, Gui Lin and Xi An. The average per capita GDP of these three cities was about 3,200 USD in 2008, ranked in the lowest quartile among all cities in China. Based on 2,899 telephone interviews, the authors find a statistically significant association between illnesses and OOP medical expenditure. However, there is no evidence suggesting that OOP medical expenditure is negatively associated with consumption on non-medical items. They attribute this non-negative association to the fast-developing Chinese economy and high level of household savings.

In contrast, using a survey consisting of 4,553 households conducted in rural China in 2002, Wang et al. (2006) find that rising OOP medical expenditure due to ill health is significantly associated with lower households' expenditures on education, social activities, savings and other expenses. The negative association is more pronounced among households with low income. However, it is worth noting that their survey was conducted before the universal coverage of public health insurance was achieved. The result may change if more recent data was used.

In a nutshell, with Wang et al. (2006) as an exception, empirical studies in China largely support the positive association between health shocks and OOP medical expenditure. Non-medical expenditure seems to be fully insured against shocks. There are less disputes among studies on China compared to studies on Vietnam, Indonesia and Sri Lanka where reduction of non-medical consumption is often found. This difference is potentially explained by the difference in income across these countries. According to the World Bank Database, in 2016, the net national income per capita was 6,309 USD in China, 3,459 USD in Sri Lanka, 2,817 in Indonesia and 1,810 in Vietnam[27]. A higher income, compared to other LMICs, may provide more resources for consumption when experiencing health shocks.

[27] These figures are in 2018 US Dollar. Data source: http://microdata.worldbank.org/index.php/home

3.4. Development of hypotheses

3.4.1. General hypothesis

Many studies have documented that households' food consumption is fully insured after the occurrence of a health shock (Mitra et al., 2016, Mohanan, 2013, Islam and Maitra, 2012). Among them, Liu (2016) and Fang et al. (2012) provide evidence on China. Liu (2016) finds that health shocks are not associated with reductions in household food consumption even prior to the universal coverage of public health insurance. A positive association between adverse health events and OOP medical expenditure is consistently found, but it does not seem to affect household's non-medical consumption[28]. For example, Fang et al. (2012) do not find any negative association between the increasing OOP medical expenditure and consumption on other non-medical items after an onset of illness.

The first wave of CHARLS was conducted in 2011, two follow-up waves were conducted in 2013 and 2015 respectively. An universal coverage of public health insurance was achieved by 2011 (Liang and Langenbrunner, 2013), and it has been playing an active role in reducing Chinese individuals' healthcare burden (Zhang et al., 2017). As such, using this dataset, I do not expect a negative association between a health shock and household's consumption on non-medical items[29]. However, I do expect a positive association between a health shock and OOP medical expenditure because the overall healthcare expenses following a health shock will increase and so does the OOP medical expenditure. I thus hypothesise that:

---

[28] Wang et al. (2006), as an exception, find that ill health reduces household investment in human capital, as well as other consumptions that are critical to human well-being in China such as expenditure on recreational items. Yet, the data used in their study was collected in 2002, when the current public health insurance schemes had not been launched and the OOP medical expenditure out of total health expenditure was as high as 58 percent.

[29] Durable consumption is excluded here. Hereafter, non-medical consumption refers to household non-durable consumption minus OOP medical expenditure. See Section 3.5 for more details.

H1: Following a health shock, Chinese households' food consumption and other non-medical consumption remain unchanged, while OOP medical expenditure increases.

3.4.2. Differentiating the effect of health shocks on OOP medical expenditure between rural and urban areas

With rapid economic development, healthcare inequalities between rural and urban areas have been rising (Wang et al., 2016). Liu et al. (1999) document that Chinese urban residents have better access to and higher utilisation of healthcare compared to their rural counterparts. There are more rural residents who do not utilise inpatient services compared to urban residents, due to rural residents' inability to pay. According to statistics released by the National Bureau of Statistics of China, in 2014, medical expenditure (OOP and non-OOP) per capita is 1,412 RMB for rural residents and 3,558 RMB for urban residents (National Bureau of Statistics of China, 2017)[30]. When a health shock hits, urban residents are likely to utilise health services more frequently than their rural counterparts. Therefore, the OOP medical expenditure, following a health shock, is likely to be higher for urban residents due to more intensive utilisation of healthcare facilities. I thus hypothesise that:

H2: In the presence of a health shock, the increase in OOP medical expenditure is higher for urban residents compared to their rural counterparts.

[30] Source: 2017 China Statistical Yearbook, compiled by the National Bureau of Statistics of China. URL: http://www.stats.gov.cn/tjsj/ndsj/2017/indexeh.htm

3.4.3. Differentiating the effect of health shocks on OOP medical expenditure between the poor and others

The poor are more vulnerable to health shocks and economic status is positively associated with the utilisation of healthcare services. Wang et al. (2018) find that, compared to others, individuals within the lowest quintile of income in CHARLS 2015 have a higher likelihood of either not seeking for healthcare or dismissing from a period of hospitalisation early. This is due to individuals with very low income being unable to afford the OOP medical cost. Among those who seek for healthcare, 30 percent of the richest (top 20 percent of per capital income distribution) seek healthcare at county or higher level hospitals, while only 15 percent of the poorest (bottom 20 percent of per capital income distribution) seek healthcare at the same level (You and Kobayashi, 2011). This reflects that the poor utilise healthcare services less intensive than the non-poor. Thus, in the presence of a health shock, the poor may experience less frequent and intensive utilisation of healthcare compared to the rich. This leads the following hypothesis:

H3: In the presence of a health shocks, individuals with lower income will experience a smaller increase in OOP medical expenditure compared to their counterparts with higher income.

3.4.4. Differentiating the effect of health shocks on OOP medical expenditure across provinces with different levels of health service access and quality

Regional differences in China are not limited to the rural-urban disparity. Residents living in some provinces have easier access to the healthcare system and receive better quality healthcare compared to those living in other provinces. According to the 2017 China Statistical Yearbook, the number of licenced doctors per 1,000 residents in Beijing was 4.11. However, this number was only 1.72 in Jiangxi province. Moreover, Fang et al. (2010) document that Beijing also has the highest number of nurses and other health workers and receives the highest funds allocated to the health sector.

The Healthcare Access and Quality (HAQ) Index, a composite index ranging from 1 (the lowest) to 100 (the highest), measures the overall personal healthcare access and quality across countries and subnational locations. The detailed methodology used to construct this index is explained in Barber et al. (2017). It is a comprehensive indicator based on raw data drawn from the Global Burden of Diseases, Injuries and Risk Factors Study. The subnational HAQ indices are available for 33 Chinese provinces and special administrative regions in 2016. China was characterised by one of the largest disparity in subnational levels of HAQ. The HAQ Index ranged from 91.5 in Beijing to 48.0 in Tibet. The gap is as high as 43.5 points. Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Liaoning, Shandong and Guangdong were provinces (municipalities) within the highest and the second highest HAQ Index deciles. Fullman et al. (2018) have shown evidence of a strong relationship between the HAQ Index and total health spending per capita. Based on this finding, I define the above-mentioned provinces (municipalities) as *provinces with higher HAQ Index* and hypotheses that:

H4: The association between health shocks and increase in OOP medical expenditure is larger for residents living in provinces with higher HAQ Index compared to residents in other provinces.

3.5. Data and summary statistics

The data is drawn from the 2011, 2013 and 2015 waves of China Health and Retirement Longitudinal Study (CHARLS). The CHARLS consists of a large nationally representative sample of individuals aged 45 or over and their spouses from 450 communities across 28 provinces in China. It is designed to be comparable with world leading studies in ageing such as the Health and Retirement Study (HRS), the English Longitudinal Study of Ageing (ELSA) and the Survey of Health, Ageing and Retirement in Europe (SHARE). It contains comprehensive information on individuals' demographics, socioeconomic status, health status and household income and expenditure. The baseline survey was conducted in 2011 with 17,708 individuals from 10,257 households being interviewed. Two follow-up waves were conducted in 2013 and 2015, respectively. 81.0 percent of the 2011 individuals were able to participate in the 2013 follow-up interviews and 2,834 new individuals were added to the 2013 sample to keep the sample's representativeness. In 2015, 574 new individuals were added to the sample and 20,517 (97.3 percent of the total 2015 sample) individuals were followed.

As health shocks are defined as either a new onset of diseases since the last wave or a 25 percent increase in physical limitations between two consecutive waves, I only include individuals who have participated in at least 2 consecutive waves of CHARLS in the present study, leading to an exclusion of about 3,500 individuals. I further exclude 1,607 individuals who are younger than 45 because this study mainly focuses on the older individuals. The final sample consists of 10,951 individuals who participated in all waves, 2,705 individuals who participated in the 2011 and 2013 waves, and 2,455 individuals who participated in the 2013 and 2015 waves. Therefore, there are 43,173 individual-wave observations in total[31].

3.5.1. Dependent variables

There is a distinction between consumption and expenditure. Consumption is the output of a home production function that uses both expenditure and time as inputs, while expenditure is the purchase of goods and services in a market setting regardless of time (Becker, 1965). Taking food consumption and expenditure as an example, following a shock which leads to a negative income change, a decline in household's food expenditure may be observed because households may reduce expenditure on eating-out or seek for better deals of food ingredients to fund rising medical expenses. However, the quantity and quality of actual food intake measured by calories intake may remain unaffected (Aguiar and Hurst, 2005). Thus, calories or macro nutrients intake from food is a better proxy of food consumption than monetary expenditure on purchasing food ingredients. In addition, after a shock, households may reduce or postpone durable expenditure to meet the need for basic consumption items. In this case, we may see a decline in household's total yearly expenditure (including expenditure on durable goods) but expenditures on non-durable items may remain unaffected. Under this circumstance, equating consumption with expenditure including durables will lead to false rejections of consumption smoothing theories. To reduce consumption volatility posed by the purchase of durable goods, in this paper, I only study changes between waves in households' yearly non-durable

[31] It is worth mentioning that, as not all individuals who participated in the baseline survey could be tracked in follow-up surveys, the concern about attrition arises. Some of the initial sampled individuals may have dropped out of following surveys due to a range of factors such as death or moving home. Attrition might lead to biased estimation of the effects of health shocks if a large amount of first-wave observations dropped out of follow-up surveys due to the incidence of health shocks. I discuss attrition in the sample I use in Section 3.5.4. In a nutshell, I do not find evidence of severe attritions existing.

consumption and its components. Besides, since the food consumption measured by calories or macro nutrients intake is not available in CHARLS, when calculating household food expenditure, I only look at food-at-home expenditure and exclude eating-out expenditure to minimise the difference between consumption and expenditure. In this setting, household expenditure is a close proxy for actual household consumption. I thus use 'consumption' and 'expenditure' interchangeably.

The impact of health shocks and the ability of households to smooth consumption may vary across different consumption items (Islam and Maitra, 2012). For example, following a health shock, the out-of-pocket medical expenditure is likely to increase while other non-food consumption items may drop to compensate for the increased medical expenditure. I thus differentiate the impact of health shocks on households' yearly food-at-home expenditure, OOP medical expenditure, non-food and non-medical expenditure, non-medical expenditure, and total non-durable expenditure, separately. The calculation and sub-components of each item is explained in Appendix 3.1.

To take into account the fact that households larger in size have higher expenditure on food, I scale food-at-home expenditure and other expenditure items that include food-at-home expenditure by household size. Thus, except for the OOP medical expenditure and household total non-durable expenditure, other expenditure items are measured at per capita level.

All money-related variables in the 2013 and 2015 waves such as household income and wealth as well as all expenditure items are deflated to the 2011 price level[32]. To reduce the possibility of the results being affected by extreme values, I dropped observations lower than

[32] I use the 2012 to 2015 provincial annual Consumer Price Index (CPI) (preceding year is 100) reported by the National Bureau of Statistics of China to deflate the 2015 values. I use the 2012 and 2013 provincial annual CPI to deflate the 2013 values.

the 1st percentile or higher than the 99th percentile for each dependent variable. It is also worth mentioning that all dependent variables are in levels in the data description and in logarithms in the regressions.

3.5.2. Health shock indicators

3.5.2.1. Onset of severe health conditions

The occurrence of severe health conditions increases largely with age (Jones et al., 2016). Since the targeted sample in this study comprises older individuals only, I use the onset of new severe health condition(s) between two survey waves as the first measure of a health shock. The onset of severe illnesses, as a measure of health shock, is well-justified by Jones et al. (2016) and Trevisan and Zantomio (2016). It is argued that this measure is less prone to reporting bias compared to other measures such as self-perceived health status differences or self-reported intensive medical service utilisations. Moreover, the incidence of severe illnesses is normally unanticipated, which reduces the concern of endogeneity of health due to the complex health and socio-economic nexus.

In CHARLS, returning individuals were asked if they had been diagnosed with any medical condition listed in the questionnaire since their last interview[33]. Following Jones et al. (2016) and Trevisan and Zantomio (2016), I identify individuals who were diagnosed with one or more acute illnesses such as cancer, heart attack and stroke since the last wave as individuals experiencing a health shock (*new_severe*=1).

[33] Full items on this condition list in CHARLS include: hypertension; dyslipidemia, diabetes, cancer or malignant tumour, chronic lung/liver/kidney disease (excluding tumours or cancer), heart attack, stroke, digestive disease, psychiatric problems, memory loss, arthritis and asthma.

Additionally, I also construct a dummy variable *new_moderate* which is equal to one if the respondents were diagnosed with one or more moderate health conditions including diabetes, hypertension, arthritis, lung/liver/kidney disease since their last interview, and zero otherwise. This is to capture the possible impact on household consumption posed by any newly-diagnosed moderate health conditions. Individuals who are diagnosed with one or more of these conditions are expected to take drugs in the long-run and thus have higher medical expenditure compared to those without.

3.5.2.2. Deterioration of mobility

The second health shock measure is based on respondents' self-reported ability to perform a set of activities of daily living (ADLs). ADL is a widely used measure of individual physical function. For the elderly, physical function is an essential indicator of general health status and has strong impact on their life satisfaction and wellbeing. Physical function measures have been tested and validated as a reliable measure of health[34].

In CHARLS, there are 20 ADLs items[35]. A score is calculated for each individual with respect to whether or not s/he had difficulty in conducting each ADL item. For example, for an ADL item X, an individual with difficulty or unable to conduct activity X scores one, and zero otherwise. A total ADL score is then calculated by summing his/her score for each ADL item. Following Gertler and Gruber (2002), I then calculate an ADL index as follows:

$$ADL\ index = \frac{(score - \min score)}{(\max score - \min score)},$$

[34] Please see Bound (1989) and Gertlet and Gruber (2002) for justifications of ADLs as a measure of health.
[35] Please see Appendix 3.2 for a list of ADLs in CHARLS.

where *score* represents each individual's total ADL score, *min score* and *max score* are respectively the minimum and maximum score in each of the yearly cross-sectional. The ADL index takes value one if the individual cannot perform any ADLs and zero if s/he can perform all ADLs without difficulty.

The second health shock indicator is constructed according to the change in the ADL index between two consecutive surveys. If an individual experiences a change in his/her ADL index larger than 0.25 since the last wave, s/he is defined as an individual experiencing a health shock (*deteriorationADL* =1)[36].

5.2.3 Other controls

In line with other studies (Liu, 2016, Zhang et al., 2017), I employ a comprehensive set of control variables in addition to the health shock variables. I include, in the regression models, respondents' age, education level, marital status, current employment status, household income and wealth, household size, home ownership, self-reported health status, as well as mental health status[37]. Considering individuals with higher health service utilisation have higher OOP medical expenditure compared to those who do not use health services, I include two dummy variables indicating respondents who did not have any inpatient visit in the last 12 months and respondents who had more than 1 inpatient visit in the last 12[38]. Table 3.1 provides detailed a definition of each variable.

[36] I also tried other benchmarks to define health shock, such as ADL score dropping by 20%, 30% and 35%, respectively. However, the results are very similar to using 25% as the benchmark.
[37] Considering the possible non-linearity of age, I included age squared in my models. However, the coefficient of age squared was almost zero. I thus excluded age squared from my models.
[38] In CHARLS, outpatient care utilisation is asked on a monthly basis and the frequency of outpatient utilisation is not recorded. The frequency of healthcare utilisation was only asked for inpatient visits. I thus cannot calculate a reliable yearly measure of utilisation of outpatient visits. As a result, the utilisation variables in this study are based on information of inpatient care usage only.

3.5.3. Summary statistics

Table 3.1 provides summary statistics and definitions of all variables. On average, yearly per capita expenditure on food-at-home, non-food non-medical expenditure per capita and non-medical expenditure per capita are 3,417 RMB, 3,729 RMB and 6,582 RMB, respectively. The average annual household OOP medical expenditure is 3,376 RMB. The average household total non-durable consumption is 22,777 RMB. 4.2 percent of the sample experience the onset of a severe conditions such as cancer, stroke and heart attack and 13.8 percent of them experience the onset of moderate chronic conditions. 7.1 percent of the sample experience a deterioration in their ADL index. The average age in my sample is around 61. 48.5 percent of the sample are male and over 80 percent of them are married. More than 20 percent of the sample are illiterate, 10 percent have completed high school and 2.3 percent have completed a bachelor's degree or above. Annual household income on average is 28,242 RMB, and household financial wealth is 14,380 RMB. The average household size is 3.2. 22.3 percent of the sample perceive their health status as excellent, very good or good and 26.2 percent perceive their health status as poor. 30.3 percent of the sample show clinical depression symptoms which is defined as CES-D score higher than 10 using the CES-D 10 items list (Andresen et al., 1994, Radloff, 1977). 86.3 percent of respondents did not make any inpatient visit in the last 12 months and 4.2 percent made more than 1 inpatient visits. 1.9 percent of the sample do not have any kinds of medical insurance.

Table 3.2 presents the differences in consumption items between individual experiencing health shocks and individuals without health shocks. The difference in OOP medical expenditure is significant. On average, individuals who experienced (did not experience) the onset of severe diseases spend 6,213 RMB (3,233 RMB) on OOP medical expenditure. The difference in OOP medical expenditure between individuals with new moderate conditions and without is 1,183 RMB. This difference between individuals with ADL deterioration and without is 2,211 RMB.

Individuals with new severe conditions spend slightly more on food compared to those without. But individuals with ADL deteriorations spend 361 RMB less on average compared to those without. The difference may be due to the fact that cooking at home would be more difficult for those who have physical limitations. Thus, food-at-home expenditure is likely to decrease following ADL deteriorations. There is no significant difference in food-at-home expenditure between individuals with new moderate conditions and those without.

Non-food and non-medical expenditure, and non-medical expenditure do not significantly differ between individuals with new conditions and without. Yet, there are statistically significant differences between these expenditures for individuals with ADL deteriorations and without. Specifically, individuals with ADL deteriorations spend 1,014 RMB and 1,443 RMB less on non-food non-medical items and on non-medical items, respectively, compared to those without.

Individuals with new medical conditions have higher household total non-durable expenditure compared to those without. This difference could be driven by the higher OOP medical expenditure for individuals with new medical conditions. Individuals with ADL deteriorations have a lower total non-durable expenditure. This can be explained considering that non-food and non-medical expenditure may drop following ADL deteriorations.

The summary statistics partially support H1. By comparing group means, individuals with health shocks have significantly higher OOP medical expenditure compared to others. However, the cross-group tabulations can only provide limited information. Expenditure on other items varies between groups, but the differences may be driven by factors other than health shocks. Thus, rigorous econometric analysis is needed.

3.5.4. Attrition in the sample

As the panel is unbalanced, the concern of attrition bias arises[39]. There exist individuals who have participated in the 2011 and 2013 waves but dropped out from the 2015 wave. These make up about 11 percent of my sample. Although this rate is relatively low considering the fact that attrition rates are often reported as 30 – 70 percent in health related surveys (Gustavson et al., 2012), it is especially problematic if the reason of dropping out from the 2015 wave survey correlates to my independent variables of interest – health shocks. Biased estimates may be obtained if the correlation between attrition and health shocks is not significantly different from zero.

Following Liu (2016), I test whether or not attrition is highly correlated with my health shocks variables by estimating the association between attrition and health shock variables conditioning on other control variables. I construct an indicator equal to 1 if an individual is a retained observation in the 2015 wave, and 0 otherwise. I then regress this indicator of attrition on all control variables as well as my health shock indicators using the OLS method with robust standard errors. The correlation between attrition and *new_severe* is significantly different from 0 with a t-value of -2.14, but small in magnitude. The correlation between attrition and *new_moderate*/*deteriorationADL* is statistically insignificant from 0 and small in magnitude. The estimated coefficients of *new_severe*, *new_moderate* and *deteriorationADL* are -0.028, -

[39] Sample representativeness may be another concern in the context of not all initial observations being followed. However, CHARLS sample was refreshed with new observations being added in each follow-up survey to ensure sample representativeness. Thus, the sample remains representative at least at the cross-sectional level.

0.008 and -0.016 respectively. The robust standard errors are 0.013, 0.007 and 0.010 respectively. This finding suggests that attrition may not pose severe biases in my estimation.

3.6. Methodology

3.6.1. Main specification

I am interested in testing the extent to which health shocks relate to different household consumption components. I estimate the following model:

$$lnC_{i,t} = \alpha_0 + \beta_1 HS_{i,t} + \boldsymbol{\gamma Controls_{i,t}} + \mu_p + \mu_t + \mu_i + \varepsilon_{i,t} \qquad (3.1)$$

where $lnC_{i,t}$is one of the following: (1) the logarithm of per capita expenditure on food at home (2) the logarithm of OOP medical expenditure; (3) the logarithm of non-food and non-medical expenditure per capita; (4) the logarithm of non-medical expenditure per capita; (5) the logarithm of total non-durable consumption, for individual *i* at time *t*. $HS_{i,t}$ is a dummy variable equal to 1 if individual *i* is exposed to a health shock at time *t*, and 0 otherwise. $\boldsymbol{Controls_{i,t}}$ is a vector of other control variables including individual *i*'s age, education level, marital status, household income and wealth, household size, home ownership, physical and mental health status, and a set of healthcare utilisation dummies. The definitions and more information on health shock indicators and other control variables are provided in Table 3.1. In line with Liu (2016) and Fang et al. (2012) who do not find consumption on non-medical items being affected after illnesses, I expect β_1 to be significantly positive when the dependent variable is the logarithm of OOP medical expenditure, and insignificant when the dependent variable is one of the other consumption items.

The error term in Equation 3.1 consists of an individual-specific component (μ_i), a time-specific component (μ_t), a provincial-specific component (μ_p), and an idiosyncratic error term ($\mu_{i,t}$). The inclusion of the time-specific component (μ_t) and provincial-specific component

(μ_p) allows for time trends and provincial differences. These are accounted for by including time and provincial dummies in all my models.

If health status is measured with errors, then taking the difference of health status between two observational periods should eliminate the concerns for time-invariant unobservable individual heterogeneity affecting the accuracy of self-reported information and/or consumption. However, it is worth mentioning that several control variables, namely education level, marital status, home ownership, household size and health status do not vary or only vary insignificantly between waves. Moreover, I am interested in testing whether or not the effect of health shocks can be differentiated according to regions and rural/urban divisions. This cannot be estimated in a fixed-effects or differencing setting as provinces where respondents reside in and urban/rural divisions do not frequently change over time. In addition, the main variable of interest, the health shock, is already measured through same individuals' health differences between two waves. This should eliminate the concern about unobserved time-invariant factors affecting the accuracy of individual self-reported information. I thus adopt a random-effects (RE) estimator. I estimate Equation 3.1 using one health shock indicator at a time, and then, use all three health indicators at the same time.

The correlations between health shock indicators are reported in Table 3.3. We can see that all health shock indicators are positively correlated. The correlation coefficient between *new_severe* and *new_moderate* is 0.120, that between *new_severe* and *deteriorationADL* is 0.085, and that between *new_moderate* and *deteriorationADL* is 0.055.

In line with H1, I expect β_1 to be positive and significantly different from zero when the dependent variable is the logarithm of OOP medical expenditure but insignificantly different from zero when the dependent variable is one of the other expenditure items.

3.6.2. Urban vs. rural residents

To test H2, I estimate the following model:

$$lnC_{i,t} = \alpha_0 + \beta_1 HS_{i,t} * rural_i + \beta_2 HS_{i,t} * (1 - rural_i) + \boldsymbol{\gamma Controls_{i,t}} + \mu_p + \mu_t + \mu_i + \varepsilon_{i,t}, \tag{3.2}$$

where $HS_{i,t} * rural$ and $HS_{i,t} * (1 - rural)$ are interactions between the health shock indicator(s) and the *rural* dummy[40]. β_1 represents the effect of health shock(s) for rural residents and β_2 represents the effect of health shock(s) for urban residents. The *Rural* dummy itself is also included as one of the control variables in Equation 3.2. For H2 to hold, we must have: $\beta_2 > \beta_1$.

3.6.3. Poor vs others

To test H3, I estimate the following model:

$$lnC_{i,t} = \alpha_0 + \beta_1 HS_{i,t} * poorest20_{i,t} + \beta_2 HS_{i,t} * \left(1 - poorest20_{i,t}\right) + \boldsymbol{\gamma Controls_{i,t}} + \mu_p + \mu_t + \mu_i + \varepsilon_{i,t}, \tag{3.3}$$

where $HS_{i,t} * poorest20$ and $HS_{i,t} * (1 - poorest20)$ are interactions between the health shock indicator(s) and the $poorest20_{i,t}$ dummy. $poorest20_{i,t}$ is a dummy variable which equals one if individual *i* has income in the bottom 20 percent of the income distribution in each wave, and 0 otherwise [41]. β_1 represents the effect of health shock(s) for the poor and β_2

[40] I estimate Equation 3.2 by putting one interaction between one health shock and the rural dummy at a time and all interactions at the same time in one regression. The results do not change. I thus report the regression results with all interactions estimated in one regression in the later section.
[41] Other benchmarks for defining the poor group are attempted. I also divide my sample into the bottom 10 percent, bottom 15 percent and bottom 25 percent and others. The results are similar.

represents the effect of health shock(s) for others. The $poorest20$ dummy itself is included as one of the control variables in Equation 3.3. For H3 to hold, we must have: $\beta_2 > \beta_1$.

3.6.4. Provinces with higher HAQ Index and others

To test H4, I estimate the following model:

$$lnC_{i,t} = \alpha_0 + \beta_1 HS_{i,t} * HAQhigh_i + \beta_2 HS_{i,t} * (1 - HAQhigh_i) + \boldsymbol{\gamma Controls_{i,t}} + \mu_p + \mu_t + \mu_i + \varepsilon_{i,t}, \tag{3.4}$$

where $HS_{i,t} * HAQhigh_i$ and $HS_{i,t} * (1 - HAQhigh_i)$ are interactions between the health shock indicator(s) and the $HAQhigh_i$ dummy. $HAQhigh_i$ is a dummy variable equal to 1 if individual *i* resides in one of the provinces with high HAQ Index, and zero otherwise[42]. β_1 represents the effect of health shock (s) for the residents in provinces with high HAQ Index and β_2 represents the effect of health shock(s) for others. $HAQhigh_i$ dummy itself is included as one of the control variables in Equation 3.4. For H4 to hold, we must have, $\beta_1 > \beta_2$.

[42] Provinces with high HAQ Index are Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Liaoning, Shandong and Guangdong.

3.7. Empirical results

3.7.1. Main results

Table 3.4 reports the RE regression results for Equation 3.1 aimed at investigating the effect of health shocks on various expenditure components. The dependent variables are one of the following: log of per capita expenditure on food-at-home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure.

Looking at the OOP medical expenditure (Panel 2) first, conditioning on other factors, individuals with a newly-diagnosed severe condition are associated with a 19.1 percent higher OOP medical expenditure. Having a newly-diagnosed moderate condition and large ADL deterioration are associated with a 10.5 percent and 9.0 percent increase in OOP medical expenditure respectively. The magnitude of such positive associations is smaller when I include all health shock indicators in one regression. In this case, having a new severe condition is associated with a 16.9 percent increase in OOP medical expenditure, and having a moderate condition and large ADL deterioration are associated with a 9.6 percent and 8.1 percent increase in OOP medical expenditure. All the associations between health shock indicators and OOP medical expenditure are statistically significant at the 1 percent level.

Including all health shock indicators in one estimation enables me to compare the effects of different health shock indicators. Having a newly-diagnosed severe condition is associated with the highest increase in OOP medical expenditure compared to that of the other two health shock indicators. ADL deterioration is associated with the lowest increase in OOP medical expenditure compared to that of the other two health shock indicators. Doctor-diagnosed conditions, compared to ADL deterioration, have a larger impact on increase in OOP medical expenditure due to the higher utilisation of health care services relating to these. By contrast, increases in limitations do not necessary indicate a higher utilisation of health care services.

My findings are consistent with those in other similar studies in which heath shocks are found to be associated with higher OOP medical expenditure and the magnitude of such associations increases with the severity of the health shocks. In the summary provided by Alam and Mahal (2014), the effect of health shocks on household OOP health spending in LMICs ranges from 0 to 34 percent, depending on the countries. My estimations fall into this range. Lindelow and Wagstaff (2005) estimate the increase in OOP health spending following a health shock in China to be 17.6 percent on average. My estimation is consistent with theirs.

Panel 1, 3 and 4 report the RE estimators for three non-medical expenditure components. *New_severe* is associated with a 4.9 to 5.4 percent increase in per capita expenditure on food-at-home and a 3.9 percent increase in non-food non-medical expenditure per capita. *New_moderate* and *DeteriorationADL* do not have statistically significant associations with any non-medical expenditure components. Since my model is designed to study the immediate change of consumption components following a health shock rather than the long-term change, it is not surprising to see an increase in expenditure on food-at-home and non-food non-medical expenditure following the onset of severe health conditions. Firstly, individuals with newly-diagnosed severe conditions may need better quality and more nutrient food to help recovery, and this may increase food bills. Secondly, utility bills, a major part of the non-food non-medical expenditure, may increase significantly for households with household members going through a severe health shock because patients may need extra heating/air-conditioning to keep warm/cool. Thirdly, elderly people with severe health conditions are likely to perceive a shorter life expectancy compared to those without. Thus, they may have strong incentives to increase consumption.

In Panel 5, *New_severe* and *new_moderate* is associated with an 8.2 and 4.0 percent increase in household total non-durable expenditure, respectively. This is likely to be driven by the increase in OOP medical expenditure following health shocks.

I find a highly significant association between experiencing a health shock and increase in OOP medical spending, with the magnitude of this association depending on the severity of health shocks. A new incidence of cancer, stroke or heart attack is associated with a 16.9-19.1 percent increase in OOP medical expenditure, while a new incidence of moderate conditions is associated with a 9.6-10.5 percent increase in OOP medical expenditure. ADL deterioration is associated with an 8.1-9.0 percent increase in OOP medical expenditure. I do not find statistically significant correlations between any of the health shock indicators and non-medical expenditures. These findings largely support H1.

Table 3.5 presents the coefficients of other control variables estimated in Equation 3.1. For brevity, I do not present coefficients of provincial and time dummies. Household income and financial wealth are associated with higher expenditures in general. Age is negatively associated with non-medical expenditures but positively associated with OOP medical expenditure. This age effect is consistent with the PIH. Household income is significantly and positively associated with all kinds of consumption, this is also consistent with the PIH as consumption is also proportionate to income. Household financial wealth shows a significantly positive association with all non-medical expenditure components, but this association is not significant for medical expenditure. Being male is positively associated with OOP medical expenditure, and also non-medical expenditures. Being married is significantly associated with

OOP medical expenditure. This may be due to the fact that OOP medical expenditure is measured at the household level, and being married means spouses' medical expenditure is also considered. Compared to being illiterate, individuals who completed a high school degree, a bachelor's degree or above are associated with higher expenditures. It is also worth mentioning that having a bachelor's degree or above is associated with a 47.9 percent (39.4 percent) higher non-food non-medical expenditure (non-medical expenditure) compared to those without. Individuals with a higher level of education may have more items in their consumption basket such as purchasing books and subscribing to newspapers and magazines, compared to others. In addition, they may have a boarder access to bank credits in the presence of any uncertainties, thus they have less incentive to save for precautionary reasons and consume more compared to others.

Individuals with excellent/very good/good self-perceived health status are associated with a higher level of non-food non-medical expenditure and a lower level of OOP expenditure. Individuals with poor self-perceived health status are associated with lower levels of food expenditure, non-food non-medical expenditure and non-medical expenditure. Poor self-perceived health is also associated with a 17.3 percent increase in OOP medical expenditure. Being clinically depressed is associated with an 8.5 percent increase in OOP medical expenditure at the 1 percent significance level and has no significant association with other expenditure components. Having no inpatient visits in the last 12 months is associated with a large decrease (58.5 percent) in the OOP medical expenditure, and having more than one inpatient visit is associated with a 22.9 percent increase in OOP medical expenditure. Having no public medical insurance is associated with decreases of OOP medical expenditure, non-food non-medical expenditure as well as non-medical expenditure.

3.7.2. The urban-rural difference

I differentiate the effect of health shocks on each consumption item between urban and rural residents by estimating Equation 3.2. I expect urban residents experiencing health shocks to show higher increase in OOP medical expenditure compared to their rural counterparts. I also expect both rural and urban residents' non-medical expenditures to remain unchanged in the presence of health shocks.

Table 3.6 reports the RE estimators of Equation 3.2. Firstly, I do not find changes in non-medical expenditure items in relation to health shocks. Secondly, I find that the association between health shocks and OOP medical expenditure is larger for urban residents. In column (2), a newly-diagnosed severe condition is associated with a 21.8 percent increase in OOP medical expenditure for urban residents, but only a 13.5 percent increase for rural residents. The onset of moderate conditions is associated with a 13.3 percent increase in OOP medical expenditure for urban residents, and a 7.4 percent increase for rural residents. Similarly, experiencing a deterioration in the ADL index is associated with a 16.1 percent increase in OOP medical expenditure in urban areas and this association is significant at the 1 percent level. I do not find a significant association between the deterioration in the ADL index and an increase of OOP medical expenditure in rural areas. Thus, H2 is supported.

From column 1 and columns 3 to 5 in Table 3.6, we can see that both rural and urban residents' consumption on non-medical items are insured against health shocks. This finding is in contrast to Wang et al. (2006) who find a negative association between illness and household non-medical expenditure in the rural China. However, it is worth noting that their data was collected in 2002 when the OOP medical expenditure share was as high as 60 percent and the public health insurance schemes were not universally available. The first wave of my data was collected in 2011 with two subsequent waves conducted in 2013 and 2015 respectively. By 2011, the universal health insurance coverage in both rural and urban areas was achieved. These schemes significantly reduce OOP medical expenditure for rural and urban residents' alike (Zhang et al., 2017), which could explain my findings. Furthermore, since the OOP medical expenditure does not increase dramatically after health shocks[43], expenditures on non-medical items remain unaffected[44].

3.7.3. Are the poor also insured against health shocks?

Table 3.7 reports the RE estimators from Equation 3.3. I do not find evidence of a negative association between health shocks and expenditure on any non-medical items. Yet, health shocks are associated with increases in OOP medical expenditures. Hence H3 is supported. Experiencing a deterioration in the ADL index is associated with an almost 10 percent increase in OOP medical expenditure for those who are not in the lowest income quintile, whilst this association is not statistically significant for the poor. As most of the limitations of ADLs are not fatal, individuals with very low income may not seek for treatment at all because of their inability to afford corresponding treatments. This low utilisation of healthcare services may limit the increase in OOP medical expenditure for the poor compared to the non-poor. The onset of a severe condition is associated with a 17.4 percent increase in OOP medical expenditure for the non-poor, and a 14.1 percent increase for the poor. This association is significant at the 1 percent level. This finding is consistent with Lindelow and Wagstaff (2005) who also find the

[43] In literature, dramatical health spending/catastrophic medical spending is defined as 40 percent increase in medical spending compared to that of last period.
[44] Reduced earnings also contribute to lowered expenditure on non-medical items. Expenditure on non-medical items could be affected by lowered labour income following health shocks. However, since my study is focused on older population in which a very large proportion of them are in retirement and do not have labour income. Thus, the income effect is small in my sample and I attribute the insignificant change of non-medical expenditure to the relatively small increase in OOP expenditure following health shocks.

increase in OOP health expenditure after a health shock to be smaller for the poor. Surprisingly, I find the poor experience a higher increase in OOP medical expenditure following the onset of moderate diseases compared to that of their non-poor counterparts. It is worth noting that, as the dependent variable Y is measured in logarithm, the coefficient of independent variable X should be interpreted as the percentage change of Y in relation to 1 unit increase in X. Thus, the larger increase in OOP medical expenditure for the poor may be caused by the fact that the OOP medical expenditure is very low for the poor prior to an onset of moderate conditions. In fact, according to statistics released by the NBS of China (National Bureau of Statistics of China, 2017), in 2014, the average medical expenditure (OOP and non-OOP) per capita is 1,412 RMB for rural residents and 3,558 RMB for urban residents. Considering poor households are clustered in rural areas, it is thus possible that, following a health shock, the poor experience a higher increase in OOP medical expenditure compared to the non-poor simply because their medical expenditure prior to the health shock is lower compared to that of the non-poor.

3.7.4. Do individuals from provinces with high HAQ Index respond to health shocks differently?

Table 3.8 reports the RE estimators from Equation 3.4. The HAQ Index measures the access to and the quality of healthcare services within a region. Provinces (municipalities) with high HAQ Index are Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Liaoning, Shandong and Guangdong. These are provinces with higher GDP, which are generally more developed compared to other provinces.

I do not find evidence for a negative association between health shocks and expenditure on non-medical items. In addition, I find health shocks are significantly associated with an increase in OOP medical expenditure and this association is significantly higher for individuals who reside in provinces with high HAQ Index. H4 is thus highly supported. Specifically, a deterioration in the ADL index is associated with a 20.5 percent increase in OOP medical expenditure for residents from provinces with high HAQ Index, but only with a 5.2 percent increase for residents from other provinces. Similarly, the onset of a severe condition is associated with a 20.8 (15.2) percent increase in OOP medical expenditure for residents from provinces with high (non-high) HAQ Index. The corresponding percentages for the onset of moderate conditions are 12.6 percent and 8.7 percent respectively.

Surprisingly, the deterioration in the ADL index is associated with an increase in OOP medial expenditure almost as high as that of the onset of a severe condition in provinces with high HAQ index. Both coefficients were significant at the 1 percent level. Recalling that, in the main specification Equation 3.1 results (Table 3.4), the coefficient associated with *deteriorationADL* is only 0.081, while that associated with *new_severe* is 0.169. Although ADL limitations are not fatal, the OOP medical expenditure still largely increases after ADL related health shocks in provinces with higher HAQ while this increase is not as large in other provinces. This difference reflects that residents from provinces with a high HAQ Index may have much higher utilisations of health care services compared to residents from other provinces. There are a few possible explanations for this difference. Firstly, individuals residing in provinces with higher HAQ Index may have better literacy and awareness of healthcare services and are therefore more likely to utilise health services when they are in need. Secondly, easier accesses to healthcare services leads to higher healthcare utilisations. Thirdly, better quality of healthcare services motivates residents to utilise these services more actively and trust healthcare providers more. Fourthly, the costs of utilising healthcare services in provinces with high HAQ Index may be higher compared to that in other provinces.

To the best of my knowledge, no existing studies have investigated the differences between regions with more developed healthcare systems and others. Thus, I cannot directly compare my findings with other studies. However, this study is consistent with Fang et al. (2012) who study the impact of illness in Western China, a region characterised by underdevelopment. In their study, they find no evidence for a negative association between illness and consumptions on non-medical items. Their finding potentially confirms that, at least in the short-run, after the incidence of adverse health events, the correlation between ill health and non-medical expenditures no longer exist in China.

3.8. Robustness tests

3.8.1. Alternative health shock indicator – new accidents

I find no evidence for a negative association between health shocks and expenditure on non-medical items for the full sample, the urban and rural subsamples, the poor and non-poor subsamples, and the high HAQ and low HAQ subsamples. I find statistically significant associations between health shocks and the increase in OOP medical expenditure for the full sample and all subsamples. Furthermore, I find this association to be higher for urban residents, non-poor residents and residents from provinces with a high HAQ Index. To check if my findings are sensitive to the selection of health shock indicators, I next adopt an alternative health shock indicator – the incidence of accidents between waves.

In CHARLS, returning respondents in the 2013 and 2015 waves were asked "*Have you even been in a traffic accident or any other kind of major accidental injury and received medical treatments since last interview?*" I identify respondents with a health shock by identifying those returning respondents who answered "*yes*" to this question.

Table 3.9 presents the number of individuals who had an accident between two waves and their average expenditure in each category. There are 1,381 respondents who have experienced an accident between two consecutive waves. This percentage is 4.87. We can see that individuals who experienced an accident since the last wave have significantly higher (1,098 RMB more) OOP medical expenditure on average. The non-medical expenditure and non-food non-medical expenditure are also, on average, higher for individuals who experienced an accident compared to those who did not. The average non-durable expenditure is higher for the group with accidents than the group without. This may be caused by the higher level of

OOP medical expenditure for those who have experienced accidents. Overall, the difference between individuals with and without a health shock is generally consistent with the summary statistics presented in the Section 3.5. Those who have experienced an accident have higher OOP medical expenditure (statistically significant at the 1 percent level), as well as higher non-food non-medical, nonmedical expenditure (statistically significant at the 10 percent level), and non-durable expenditure (statistically significant at the 5 percent level) compared to others.

Table 3.10 reports the coefficient of all control variables (excluding provincial and time dummies) obtained by estimating Equation 3.1 and using *newaccident* as the health shock indicator. H1 is supported. *newaccident* is associated with an increase in OOP medical expenditure but there is no evidence suggesting an association between *newaccident* and expenditure on any non-medical items. The coefficients of other variables are also highly consistent with results reported in Table 3.5.

Table 3.11 reports the coefficient of interactions between health shock indicators and each subsample divider. The significant association between *newaccident* and the increase in OOP medical expenditure can be confirmed for both rural and urban residents. However, the magnitude of such an association is very similar for both groups. The association between *newaccident* and the increase in OOP expenditure is significant for the non-poor, but insignificant for the poor. The insignificance for the poor may be caused by the small number of eligible observations as there are only few individuals who fall in the lowest income quintile and have an accident in the same year (N=253). Finally, the health shock - OOP expenditure association is higher for individuals who reside in provinces with high HAQ Index than without.

3.8.2. Propensity score matching

To ensure that individuals with and without a health shock are as comparable as possible, I apply the propensity score matching (PSM) method developed by Rosenbaum and Rubin (1983). Each individual who has experienced a health shock (*treated group*) since the last wave is matched with another individual who has not in fact experienced such a shock but has a similar likelihood of having one (*matched control group*). The likelihood of experiencing a health shock is estimated based on a set of individual characteristics including age, gender, education level and so on. Thus, two individuals who are matched in a pair share similar characteristics and have the same likelihood of having a health shock. I then compare each expenditure category between the treated group and matched control group. In this way, the concern of individual heterogeneity is reduced to the extent that at least observed differences between the treated and control groups are controlled for.

I firstly use a probit model to estimate the probability of experiencing a health shock conditioning on a set of observable variables $\boldsymbol{X}$. The health shock are, in turn, new onset of severe conditions between two consecutive waves (*new_severe*), new onset of moderate conditions between two consecutive waves (*new_moderate*), and large deterioration of ADLs between two consecutive waves (*deteriorationADL*)[45]. $\boldsymbol{X}$ include age, gender, marital status, educational dummies, household income, wealth, household size, home ownership, self-perceived health status, a depression indicator, inpatient care utilisation dummies, as well as provincial and time dummies. To achieve a better balance across all observable characteristics between the treated and control groups, I also include the quadratic terms of all continuous variables (i.e. age, income, wealth and household size) (Imbens and Wooldridge, 2007). The

[45] There are defined in Section 3.5.2.

estimated probability of experiencing a health shock (*D=1*) conditioning on $\boldsymbol{X}$ is the propensity score *(Pr(D=1|$\boldsymbol{X}$))*. The average treatment effect on the treated (ATT) is defined as:

$$ATT = E(Y_1|\boldsymbol{X}, D = 1) - E(Y_0|\boldsymbol{X}, D = 1) \tag{3.5}$$

where Y_1 denotes a certain category of expenditure for individuals with a health shock, and Y_0 denotes that for individuals without a health shock. $E(Y_0|\boldsymbol{X}, D = 1)$ is the counterfactual (the amount of an individual who did experience a health shock would have consumed if s/he did not experience one). This is obviously not observable. Based on estimated propensity scores, I pair up two or more individuals with the same or similar likelihood of having a health shock depending on the matching algorithms. I then use the expenditure of a matched individual who did not experience a health shock but has the same or closest likelihood of having one as a proxy for $E(Y_0|\boldsymbol{X}, D = 1)$.

Several matching algorithms can be used, such as one-to-one matching, k-nearest neighbours matching, calliper or radius matching, and kernel matching. Following García-Gómez (2011), once the propensity score is estimated, I use the Epanechnikov kernel algorithm with replacement to calculate the ATT. Kernel matching assigns weights for all individuals in the control group. The weight depends on the difference in the estimated propensity score between the treated and control individuals. Kernel matching is recommended when the size of the control group is large because it gains better precision and lower variance in estimates (Caliendo and Kopeinig, 2005).

Using kernel matching method[46], the quality of matching is presented in Appendix 3.3. The test of covariate balance is conducted using Stata 15 command pstest. %bias is the percentage difference of the sample means in the treated and matched groups as a percentage of the square root of the average of the sample variances in the treated and matched groups. Mean and median bias are the mean and median of the distribution of bias. The smaller these values are, the better matching is achieved. T-tests are conducted for comparing the mean differences between the treated and matched control groups after matching. Appendix Table 3.3 show that the differences in covariances between the treated and matched groups are not statistically significant, indicating good matchings. The %biases are generally small. The values of Rubin's B and Rubin's R are 15.1 and 0.99 respectively. Rubin (2001) recommends B less than 25 and R between 0.5 and 2 for the samples to be sufficiently balanced. Figure 3.3a and 3.3b show graphs of the estimated propensity score before and after matching. We can see that the estimated propensity score distributions for the treated and matched control groups are very close after matching.

Table 3.12 reports the ATT of health shocks between the treated and control groups using kernel matching. The difference in OOP medical expenditure is highly significant between groups with and without health shocks. Specifically, individuals with an onset of new severe conditions have 1,997 RMB higher OOP medical expenditure than those without. Individuals with an onset of new moderate conditions/deterioration of ADLs have 619/1,074 RMB higher OOP medical expenditure than those without. Thus, H1 is largely supported. I do not find statistically significant differences in consumption on non-medical items between treated and matched groups, except for one case – compared to those who without, individuals with large

[46] My results do not change when other matching algorithms are adopted. Kernel matching results are reported due to its achievement of better precision. Caliendo and Kopeinig (2005) provide comprehensive comparisons among all matching algorithms.

deterioration of ADLs, on average, have a 200 RMB lower expenditure on non-food non-medical items. It is worth noting that commuting and recreational expenditures are components of the *nonfoodmedpc*. Individuals with deterioration of ADLs are characterised by limited mobility, thus, their commuting and recreational expenditures are likely to be lower compared to those who without limitations.

The PSM method has several limitations. First, the propensity score is estimated in a cross-sectional setting, thus one cannot take advantage of the panel data structure. Second, results obtained from matchings in two different subgroups are not directly comparable. For example, I could conduct PSM in the rural and urban subsample, separately. But comparing the ATTs obtained from each subsample is problematic because the observations from the rural subsample are not matched with individuals from the urban subsample. Thus, these two observations are not comparable across subsamples. This prevents me from differentiating the effect of health shocks between rural and urban residents, between the poor and the non-poor, and between provinces with high/low HAQ Index.

To address this problem, following Berger et al. (2005), I construct a new sample after estimating the propensity score by only keeping the matched observations. Next, I perform a set of RE regressions using the new sample to estimate Equation 3.2 to Equation 3.4. It is argued that running regressions in a matched sample can increase efficiency (Rubin and Thomas, 2000, Berger et al., 2005).

Here, I adopt the one-to-one neatest neighbour matching instead of the kernel matching to construct my matched sample because running RE regressions after a kernel matching requires accommodating the weight of each matched individual in each regression. However, the kernel method does not generate a consistent weight for each matched individual across waves. I thus adopt the one-to-one nearest neighbour matching to construct the matched sample. I use *new_severe, new_moderate, DeteriorationADL* in turn as the treatment. After each matching, I only keep treated and matched observations. Hence, I have three new datasets with each health shock as the treatment. I then estimate Equation 3.2 to 3.4 using each constructed sample.

Table 3.13 reports the coefficients of interactions between the health shock indicators and subsample dividers. It is worth noting that I only include interactions of one health shock indicator at a time because different constructed samples are used for different treatments. Using constructed samples, I find the association between a health shock and OOP medical expenditure to be larger for urban than rural residents. Probably due to the low level of healthcare utilisation in rural areas, the association between health shocks and OOP medical expenditure is smaller for the rural residents. Hence, H2 is strongly supported.

I find that the poor show a higher increase in OOP medical expenditure following a health shock (defined as onset of new conditions) compared to the non-poor. The exception is that, the association between ADL deterioration and the increase in OOP expenditure is not significant and smaller for the poor compared to the non-poor. Again, since severe and moderate conditions require more compulsory treatments than ADL deteriorations, OOP medical expenditure may increase more for the poor because they have a lower level of OOP medical expenditure prior to the onset of new conditions than the non-poor. In addition, as ADL deterioration is not fatal, the poor may not seek for treatments and that leads to insignificant and much lower increase in OOP medical expenditure compared to the non-poor. H3 is therefore only partly supported.

In general, residents from high HAQ index provinces show higher OOP medical expenditure following a health shock. However, after the onset of a severe condition, residents from provinces with high HAQ index show a slightly lower increase in OOP medical expenditure compared to those who reside in other provinces. More generous reimbursement rates of public health insurance schemes in provinces with high HAQ Index could potentially explain this difference. Thus, H4 is only partly supported.

3.9. Conclusion

Using the 2011, 2013 and 2015 waves of the China Health and Retirement Longitudinal Study (CHARLS), this paper investigates the extent to which households' consumption profile changes after a health shock. Following existing studies in the literature, I define health shocks as the onset of severe medical conditions, the onset of moderate medical conditions, as well as a large deterioration in the ADL index.

I document that health shocks are associated with an 8.1-19.1 percent increase in OOP medical expenditure for Chinese individuals aged 45 and over. The magnitude of this association depends on the selection of health shock indicators and model specifications. Following a health shock, expenditure on non-medical items remains unchanged, indicating Chinese households' non-medical consumption is insured against health shocks.

Moreover, I find that the association between health shocks and the increase in OOP expenditure to be stronger for urban residents compared to their rural counterparts. This finding may reflect underutilisation of healthcare services by rural residents. I also find a larger increase in OOP expenditure following a health shock for the poor compared to the non-poor. This could be explained considering that the poor have a lower level of OOP expenditure compared to the non-poor prior to shocks. Although I do not find evidence of expenditure on non-medical items being affected even for the poor, if the health shock is severe and persistent, the poor's non-medical expenditures may have to be compromised to accommodate the large increase in OOP expenditure. I also find evidence that the poor may not utilise the healthcare system enough if the shocks are not fatal. In addition, I find evidence of provincial disparities. The association between health shocks and the increase in OOP medical expenditure is higher in provinces with better healthcare systems. For instance, in the presence of a deterioration of the ADL index, the increase in OOP medical expenditure is almost 3 times higher for those who reside in provinces with a better healthcare system. This finding suggests a higher level of healthcare service utilisation in provinces with a more developed healthcare system.

My findings suggest that, in China, non-medical consumption is generally insured in the presence of health shocks. OOP medical expenditure increases significantly after health shocks, but the extent of this increase is not dramatic. These findings are consistent with Fang et al. (2012) and Liu (2016). However, the insignificant change in non-medical consumption and the relatively small increase in OOP medical expenditure following health shocks might be resulted from low utilisations of healthcare services.

Policy makers should deepen the coverage of public health insurance schemes targeted on special groups such as the rural residents and the poor to boost their healthcare service utilisations. In addition, policies should be designed to reduce disparities in healthcare systems across provinces.

3.10. Limitations and future research possibilities

There are several limitations of the present study. First, this study is only focused on immediate changes of expenditure items due to data limitations. It leaves the more complicated modelling for long-run effects of health shocks to future research. This could be done by applying a dynamic framework similar to the one presented in Chapter Four. Second, since the definition of *household member* is unclear in CHARLS and inconsistent between waves, the household compositions cannot be clearly identified. Thus, although I am aware that household consumption profile is sensitive to changes in composition of household members, I cannot include the changes of household compositions in my model. Third, the household head is not clearly identified in CHARLS, and I can only identify the main respondent of each household. However, it is unclear if this main respondent is the household head or not. This is because in CHARLS surveys, the main respondent is randomly chosen in each household as long as s/he is aged 45 or over. To avoid misidentifying the household head, the observations in sample are kept at the individual level instead of household level.

At last, this study does not investigate the reasons why non-medical expenditure is not affected in the presence of health shocks due to data limitations. In the literature, savings, formal and informal borrowings, family transfers and selling assets can be viewed as potential coping strategies for households exposed to health shocks to secure their non-medical expenditure (Kruk et al., 2009, Sparrow et al., 2013, Modena and Gilbert, 2011). However, the valid number of non-missing observations for saving and borrowing related variables is very small in CHARLS. In addition, family transfers are categorised and surveyed differently across waves. It is thus difficult for me to calculate household savings, borrowings and family transfers for each wave consistently.

Future research will focus on studying the dynamics of household consumption profile following a health shock in a longer-run setting. Furthermore, I will further explore Chinese households' coping strategies in the presence of health shocks once relevant saving, borrowing and family transfer variables become more reliable in CHARLS.

Table 3. 1 Summary statistics

	Description	Type	Mean	S.D.
Dependent variables				
foodinpc	Per capita expenditure on food at home	Continuous	3.417	3.374
medicalexp	Household total medical expenditure	Continuous	3.376	6.706
nonfoodmedpc	Non-food, non-medical expenditure per capita	Continuous	3.729	4.729
nonmedpc	Non-medical expenditure per capita	Continuous	6.582	6.691
nondurable	Household total non-durable consumption	Continuous	22.777	21.279
Health shock indicators				
new_severe	New onset of severe condition(s) [1]; other [0]	Dummy variable	0.042	0.371
new_moderate	New onset of moderate condition(s) [1]; other [0]	Dummy variable	0.138	0.344
deteriorationADL	ADL index dropped by more than 25% [1]; other [0]	Dummy variable	0.071	0.257
Other controls				
age	Respondent's age	Continuous	61.070	9.690
male	Male [1]; female[0]	Dummy variable	0.485	0.500
married	Married [1]; other [0]	Dummy variable	0.820	0.384
widowed	Widowed [1]; other [0]	Dummy variable	0.109	0.313
illiterate	Illiterate [1]; other [0]	Dummy variable	0.261	0.439
highschool	Completed high school [1]; other [0]	Dummy variable	0.102	0.302
highedu	Completed bachelor's degree or above [1]; other [0]	Dummy variable	0.023	0.150
hhitot	Total household income	Continuous	28.242	33.976
hhfinassets	Total household financial wealth	Continuous	14.380	35.050
stillworking	Still working [1]; other[0]	Dummy variable	0.670	0.471
hhsize	Household size	Continuous	3.212	1.623
homeowner	Home owner [1]; other [0]	Dummy variable	0.888	0.316
goodhealth	Excellent/very good/good self-perceived health status [1]; other[0]	Dummy variable	0.223	0.417
poorhealth	Poor self-perceived health status [1]; other [0]	Dummy variable	0.262	0.440
depressed	Depressed (CES-D score $\geq$10) [1]; other [0]	Dummy variable	0.303	0.460
noinpatientcare	No inpatient visit in last 12 months [1]; other [0]	Dummy variable	0.862	0.345
mt1inpatientcare	More than 1 inpatient visits in last 12 months [1]; other [0]	Dummy variable	0.042	0.202
noinsurance	No medical insurance [1]; other [0]	Dummy variable	0.019	0.140

Notes: S.D. denotes standard deviation. The various components of the dependent variables are listed in Appendixes 3.1. Severe conditions include cancer, stroke and heart attack. Moderate conditions include diabetes, hypertension, arthritis, lung/liver/kidney disease. Total number of observations is 43,173. *foodinpc, medicalexp, nonfoodmedpc, nonmedpc, nondurable, hhitot, hhfinassets* are stated in 1,000 RMB (2011 price level).

Table 3. 2 Comparison of consumption components between individuals with health shocks and without

Variables	*New_severe =0*	*New_severe =1*	*Diff*	*New_moderate =0*	*New_moderate =1*	*Diff*	*D.ADL =0*	*D.ADL =1*	*Diff*
foodinpc	3.377	3.704	-0.328***	3.398	3.338	0.059	3.412	3.05	0.361***
medicalexp	3.233	6.213	-2.979***	3.191	4.373	-1.183***	3.206	5.417	-2.211***
nonfoodmedpc	3.643	3.709	-0.066	3.651	3.617	0.034	3.717	2.702	1.014***
nonmedepc	6.482	6.685	-0.203	6.507	6.388	0.118	6.59	5.147	1.443***
nondurable	22.326	26.277	-3.951***	22.347	23.364	-1.017***	22.597	21.235	1.362***
No. of observation									

Notes: *Diff* denotes the p-value of a t-test for the mean difference between the two groups. *** indicates statistical significance at the 1% level.

Table 3. 3 Correlation Matrix between health shocks

	New_severe	*New_moderate*	*DetariorationADL*
New_severe		0.120*	0.085*
New_moderate	0.120*		0.055*
DetariorationADL	0.085*	0.055*	

Notes: Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman’s rank correlation. * denotes statistical significance is at the 5% level.

Table 3. 4 Health shocks and consumption: RE estimates

Health shock indicators	Consumption components			
Panel 1	**log (food expenditure p.c.)**			
New_severe	0.049**			0.054***
	(0.020)			(0.021)
New_moderate		0.004		0.004
		(0.011)		(0.011)
DetariorationADL			-0.015	-0.017
			(0.017)	(0.017)
Panel 2	**log (medical expenditure)**			
New_severe	0.191***			0.169***
	(0.030)			(0.031)
New_moderate		0.105***		0.096***
		(0.016)		(0.017)
DetariorationADL			0.090***	0.081***
			(0.026)	(0.026)
Panel 3	**log (non-food non-medical expenditure p.c.)**			
New_severe	0.039*			0.033
	(0.021)			(0.021)
New_moderate		0.019		0.019
		(0.012)		(0.012)
DetariorationADL			-0.014	-0.016
			(0.017)	(0.017)
Panel 4	**log (non-medical expenditure p.c.)**			
New_severe	0.029			0.030
	(0.022)			(0.022)
New_moderate		0.012		0.010
		(0.012)		(0.012)
DetariorationADL			-0.018	-0.021
			(0.018)	(0.018)
Panel 5	**log (non-durable expenditure)**			
New_severe	0.089***			0.082***
	(0.026)			(0.027)
New_moderate		0.045***		0.040***
		(0.014)		(0.014)
DetariorationADL			0.029	0.025
			(0.023)	(0.023)

Notes: * indicates statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Dependent variables are one of the following: log of per capita expenditure on food at home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure. Other control variables include all regressors defined and listed in Table 3.1. Provincial dummies and a wave dummy are included in all regressions. The first three columns report estimations of Equation 3.1 using one health shock indicator at a time, and the fourth column reports estimation of Equation 3.1 using all health shock indicators at once.

Table 3. 5 Coefficients of other control variables: RE estimates

	lfoodpc (1)	*lmedicalexp* (2)	*lnonfoodmedpc* (3)	*lnonmedpc* (4)	*lnondurable* (5)
lhhitot	0.075***	0.041***	0.117***	0.128***	0.141***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)
lhhfinassets	0.036***	-0.007	0.048***	0.066***	0.066***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
age	-0.005***	0.003***	-0.015***	-0.015***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
male	-0.010*	0.017**	0.017***	0.012**	0.021***
	(0.005)	(0.008)	(0.006)	(0.006)	(0.008)
married	-0.028	0.152***	-0.040*	-0.005	0.185***
	(0.020)	(0.025)	(0.023)	(0.022)	(0.025)
widowed	0.028	-0.058*	0.053*	0.008	0.009
	(0.025)	(0.031)	(0.028)	(0.028)	(0.033)
illiterate	-0.069***	-0.017	-0.077***	-0.087***	-0.090***
	(0.011)	(0.016)	(0.012)	(0.012)	(0.015)
highschool	0.108***	0.061***	0.161***	0.164***	0.169***
	(0.015)	(0.022)	(0.017)	(0.016)	(0.018)
highedu	0.265***	0.079*	0.479***	0.394***	0.381***
	(0.032)	(0.046)	(0.042)	(0.036)	(0.039)
hhsize	-0.096***	0.034***	-0.089***	-0.112***	0.119***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
stillworking	-0.123***	-0.107***	-0.068***	-0.096***	-0.130***
	(0.010)	(0.015)	(0.011)	(0.011)	(0.014)
homeowner	-0.003	-0.005	0.017	-0.007	0.011
	(0.017)	(0.023)	(0.018)	(0.017)	(0.021)
goodhealth	0.013	-0.131***	0.032***	0.019*	-0.007
	(0.010)	(0.014)	(0.011)	(0.011)	(0.013)
poorhealth	-0.039***	0.173***	-0.028***	-0.052***	-0.011
	(0.010)	(0.015)	(0.011)	(0.011)	(0.013)
depressed	-0.014	0.085***	-0.012	-0.010	0.019
	(0.010)	(0.014)	(0.010)	(0.010)	(0.012)
noinpatientcare	-0.042***	-0.585***	0.001	-0.016	-0.172***
	(0.013)	(0.022)	(0.014)	(0.014)	(0.017)
mt1inpatientcare	-0.012	0.229***	0.028	0.024	0.135***
	(0.023)	(0.037)	(0.023)	(0.024)	(0.029)
noinsurance	-0.028	-0.097**	-0.067*	-0.086**	-0.137***
	(0.038)	(0.049)	(0.039)	(0.040)	(0.051)
Constant	1.880***	1.044***	2.120***	2.662***	3.040***
	(0.060)	(0.091)	(0.070)	(0.067)	(0.081)
Observations	21,372	22,917	21,291	24,405	24,390

Notes: * indicates statistical significance is at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Provincial dummies and one wave dummy are included in all regressions. Other control variables include a full set of health shock indicators. 1% outliers at each tail are dropped for all dependent variables as well as continuous control variables including *lhhitot, lhhfinassets.* Outliers for the variable *hhsize* are dropped for the top 1% only. Individuals who are younger than 45 are excluded from the analysis. Definitions of all variables are presented in Table 3.1.

Table 3. 6 Rural vs. urban

	(1) *lfoodpc*	(2) *lmedicalexp*	(3) *lnonfoodmedpc*	(4) *lnonmedpc*	(5) *lnondurable*
ADL_rural	-0.009	0.049	-0.010	-0.009	0.039
	(0.021)	(0.030)	(0.020)	(0.022)	(0.028)
ADL_urban	-0.017	0.161***	-0.020	-0.034	0.006
	(0.029)	(0.048)	(0.031)	(0.031)	(0.040)
severe_rural	0.050*	0.135***	0.025	0.029	0.081**
	(0.027)	(0.038)	(0.028)	(0.029)	(0.035)
severe_urban	0.057*	0.218***	0.042	0.029	0.082**
	(0.030)	(0.050)	(0.034)	(0.034)	(0.041)
moderate_rural	0.012	0.074***	0.036**	0.020	0.044**
	(0.014)	(0.020)	(0.016)	(0.016)	(0.018)
moderate_urban	-0.010	0.133***	-0.010	-0.008	0.032
	(0.018)	(0.029)	(0.020)	(0.020)	(0.023)
Observations	21,372	22,917	21,291	24,405	24,390
Number of id	14,117	14,682	14,080	15,180	15,174

Notes: * indicates statistical significance is at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Dependent variables are one of the following: log of per capita expenditure on food-at-home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure. Other control variables include all regressors defined and listed in Table 3.1. Provincial dummies and a wave dummy are included in all regressions.

Table 3. 7 The poor vs. non-poor

	(1)	(2)	(3)	(4)	(5)
	lfoodpc	*lmedicalexp*	*lnonfoodmedpc*	*lnonmedpc*	*lnondurable*
ADL_poorest20	-0.020	0.026	-0.002	-0.063	-0.019
	(0.037)	(0.053)	(0.036)	(0.039)	(0.050)
ADL_other	-0.016	0.099***	-0.021	-0.006	0.040
	(0.019)	(0.029)	(0.019)	(0.020)	(0.025)
severe_poorest20	0.084	0.141**	0.068	0.034	0.078
	(0.053)	(0.071)	(0.048)	(0.054)	(0.068)
severe_ other	0.048**	0.174***	0.026	0.029	0.083***
	(0.022)	(0.034)	(0.024)	(0.024)	(0.029)
moderate_poorest20	-0.012	0.142***	0.005	-0.006	0.045
	(0.026)	(0.037)	(0.027)	(0.028)	(0.034)
moderate_ other	0.008	0.084***	0.023*	0.013	0.039**
	(0.012)	(0.019)	(0.014)	(0.014)	(0.016)
Observations	21,372	22,917	21,291	24,405	24,390
Number of id	14,117	14,682	14,080	15,180	15,174

Notes: * indicates statistical significance is at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Dependent variables are one of the following: log of per capita expenditure on food-at-home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure. Other control variables include all regressors defined and listed in Table 3.1. Provincial dummies and a wave dummy are included in all regressions. *Poorest20* is a dummy variable equal to 1 if the individual falls within the lowest quintile income of each wave, and 0 otherwise.

Table 3. 8 Province with higher HAQ index vs. provinces without

	(1)	(2)	(3)	(4)	(5)
	lfoodpc	*lmedicalexp*	*lnonfoodmedpc*	*lnonmedpc*	*lnondurable*
ADL_HAQhigh	-0.026	0.205***	-0.017	-0.056	0.040
	(0.039)	(0.063)	(0.041)	(0.041)	(0.052)
ADL_noHAQhigh	-0.016	0.052*	-0.017	-0.013	0.019
	(0.019)	(0.028)	(0.019)	(0.020)	(0.025)
severe_HAQhigh	0.109***	0.208***	0.103**	0.105**	0.177***
	(0.039)	(0.066)	(0.043)	(0.045)	(0.055)
severe_noHAQhigh	0.037	0.152***	0.011	0.008	0.052*
	(0.024)	(0.034)	(0.025)	(0.025)	(0.031)
moderate_HAQhigh	-0.033	0.126***	0.013	-0.033	0.015
	(0.023)	(0.035)	(0.025)	(0.025)	(0.030)
moderate_noHAQhigh	0.016	0.087***	0.021	0.023	0.048***
	(0.013)	(0.019)	(0.014)	(0.014)	(0.016)
Observations	21,372	22,917	21,291	24,405	24,390
Number of id	14,117	14,682	14,080	15,180	15,174

Notes: * indicates statistical significance is at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Dependent variables are one of the following: log of per capita expenditure on food-at-home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure. Other control variables include all regressors defined and listed in Table 3.1. Provincial dummies and a wave dummy are included in all regressions. *HAQhigh* is a dummy variable equal to 1 if the individual resides in are Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Liaoning, Shandong and Guangdong, and 0 otherwise.

Table 3. 9 New accident – an alternative measure of health shocks

	New accidents (1) (N=1,381)	No accidents (2) (N=28, 324)	Diff (1)-(2)
foodinpc	3.481	3.415	0.066
medicalexp	4.422	3.324	1.098***
nonfoodmedpc	3.978	3.719	0.260*
nonmedepc	6.936	6.568	0.368*
nondurable	24.198	22.715	1.483**

Notes: *Diff* denotes the p-value of a t-test for the mean difference between two groups. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 1% level. All values are converted according to the 2011 price level. The unit is 1,000 RMB.

Table 3. 10 Coefficients of *newaccident* and other variables on consumption components

	(1) *lfoodpc*	(2) *lmedicalexp*	(3) *lnonfoodmedpc*	(4) *lnonmedpc*	(5) *lnondurable*
newaccident	-0.006	0.082***	0.031	0.027	0.056**
	(0.018)	(0.026)	(0.020)	(0.020)	(0.023)
lhhitot	0.075***	0.039***	0.117***	0.129***	0.142***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)
lhhfinassets	0.037***	-0.006	0.049***	0.067***	0.067***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
age	-0.005***	0.003***	-0.016***	-0.015***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
male	-0.008	0.017**	0.018***	0.014**	0.022***
	(0.005)	(0.008)	(0.006)	(0.006)	(0.007)
married	-0.027	0.152***	-0.026	0.001	0.189***
	(0.019)	(0.024)	(0.021)	(0.021)	(0.024)
widowed	0.029	-0.052*	0.076***	0.018	0.020
	(0.024)	(0.030)	(0.027)	(0.026)	(0.031)
illiterate	-0.070***	-0.012	-0.078***	-0.087***	-0.091***
	(0.010)	(0.015)	(0.011)	(0.012)	(0.014)
highschool	0.119***	0.053**	0.162***	0.163***	0.167***
	(0.014)	(0.021)	(0.017)	(0.016)	(0.018)
highedu	0.253***	0.072*	0.485***	0.376***	0.363***
	(0.030)	(0.044)	(0.041)	(0.035)	(0.039)
hhsize	-0.097***	0.037***	-0.090***	-0.113***	0.119***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)
stillworking	-0.123***	-0.115***	-0.066***	-0.095***	-0.131***
	(0.010)	(0.014)	(0.011)	(0.011)	(0.013)
homeowner	-0.006	0.007	0.016	-0.004	0.014
	(0.016)	(0.022)	(0.017)	(0.017)	(0.020)
goodhealth	0.013	-0.134***	0.031***	0.019*	-0.010
	(0.010)	(0.014)	(0.011)	(0.010)	(0.012)
poorhealth	-0.034***	0.190***	-0.023**	-0.046***	0.001
	(0.009)	(0.014)	(0.010)	(0.010)	(0.012)
depressed	-0.013	0.087***	-0.017*	-0.015	0.014
	(0.009)	(0.013)	(0.010)	(0.010)	(0.012)
noinpatientcare	-0.040***	-0.596***	-0.004	-0.014	-0.174***
	(0.013)	(0.021)	(0.014)	(0.014)	(0.017)
mt1inpatientcare	-0.008	0.247***	0.028	0.027	0.141***
	(0.022)	(0.036)	(0.022)	(0.023)	(0.028)
noinsurance	-0.018	-0.135***	-0.051	-0.080**	-0.144***
	(0.034)	(0.042)	(0.035)	(0.035)	(0.045)
Constant	1.885***	1.079***	2.168***	2.687***	3.072***
	(0.057)	(0.087)	(0.067)	(0.064)	(0.077)
Observations	23,571	25,291	23,476	26,926	26,907
Number of id	14,588	15,056	14,551	15,470	15,469

Notes: * indicates statistical significance is at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Dependent variables are one of the following: log of per capita expenditure on food-at-home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure. Other control variables include all regressors defined and listed in Table 3.1. Provincial dummies and a wave dummy are included in all regressions.

Table 3. 11 Coefficients of interactions between *newaccident* and subsample dividers

	(1) *lmedicalexp*	(2) *lmedicalexp*	(3) *lmedicalexp*
newaccident_rural	0.080**		
	(0.033)		
newaccident_urban	0.087**		
	(0.042)		
newaccident_poorest20		0.092	
		(0.063)	
newaccident_nonpoor		0.080***	
		(0.029)	
newaccident_HAQhigh			0.138***
			(0.051)
newaccident_noHAQhigh			0.061**
			(0.030)
Observations	25,291	25,291	25,291
Number of id	15,056	15,056	15,056

Notes: * indicates statistical significance is at the 10% level, ** at the 5% level, *** at the 1% level. Robust standard errors are in parentheses. Dependent variables are one of the following: log of per capita expenditure on food-at-home, log of medical expenditure, log of non-food and non-medical expenditure per capita, log of non-medical expenditure per capita, and log of household total non-durable expenditure. Other control variables include all regressors defined and listed in Table 3.1. Provincial dummies and a wave dummy are included in all regressions. *Poorest20* is a dummy variable equal to 1 if the individual's income is in the lowest quintile of income in each wave, and 0 otherwise. *HAQhigh* is a dummy variable equal to 1 if the individual reside in are Beijing, Tianjin, Shanghai, Zhejiang, Jiangsu, Liaoning, Shandong and Guangdong, and 0 otherwise.

Table 3. 12 ATT of health shock indicators after propensity score matchings

Variables	*New_severe*			*New_moderate*			*DeteriorationADL*		
	Treated	Control	Diff	Treated	Control	Diff	Treated	Control	Diff
foodinpc	3.719	3.387	0.332***	3.330	3.318	0.012	3.064	3.098	-0.034
medicalexp	6.314	4.317	1.997***	4.376	3.757	0.619***	5.395	4.320	1.074***
nonfoodmedpc	3.664	3.506	0.158	3.524	3.438	0.086	2.721	2.920	-0.200*
nonmedepc	6.655	6.288	0.366*	6.300	6.206	0.093	5.190	5.387	-0.196
nondurable	26.323	22.639	3.684***	23.021	22.104	0.917**	21.224	20.186	1.038*

Notes: A Kernel matching algorithm is adopted. Diff is the mean difference between the treated group and control group. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 1% level. Number of treated (T) and controls (C): *foodinpc*: T_{new_severe}=897, C_{new_severe}=21,255, $T_{new\_moderate}$=3,045, $C_{newe\_moderate}$=19,109, T_{ADL}=1,368, C_{ADL}=20,055, *medicalexp*: T_{new_severe}=962, C_{new_severe}=22,793, $T_{new\_moderate}$=3,299, $C_{newe\_moderate}$=20,459, T_{ADL}=1,513, C_{ADL}=21,456, *nonfoodmedpc*: T_{new_severe}=892, C_{new_severe}=21,172, $T_{new\_moderate}$=3,032, $C_{newe\_moderate}$=19,034, T_{ADL}=1,363, C_{ADL}=19,979, *nonmedepc*: T_{new_severe}=1,042, C_{new_severe}=24,268, $T_{new\_moderate}$=3,501 $C_{newe\_moderate}$=21,812, T_{ADL}=1,651, C_{ADL}=22,810, *nondurable*: T_{new_severe}=1,038, C_{new_severe}=24,259, $T_{new\_moderate}$=3,500, $C_{newe\_moderate}$=21,800, T_{ADL}=1,645, C_{ADL}=22,800.

Table 3. 13 Estimates of interactions using constructed datasets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lmedicalexp	*lmedicalexp*	*lmedicalexp*	*lmedicalexp*	*lmedicalexp*	*lmedicalexp*	*lmedicalexp*	*lmedicalexp*	*lmedicalexp*
severe_rural	0.184***								
	(0.0517)								
severe_urban	0.247***								
	(0.0700)								
severepoorest20		0.319***							
		(0.0889)							
severenopoorest20		0.184***							
		(0.0466)							
severe_HAQhigh			0.191**						
			(0.0947)						
severe_noHAQhigh			0.215***						
			(0.0459)						
moderate_rural				0.115***					
				(0.0269)					
moderate_urban				0.154***					
				(0.0380)					
moderatepoorest20					0.182***				
					(0.0493)				
moderatenopoorest20					0.116***				
					(0.0248)				
moderateHAQhigh						0.159***			
						(0.0457)			
moderatenoHAQhigh						0.121***			
						(0.0251)			
ADL_rural							0.0567		
							(0.0412)		

ADL_urban							0.224***		
							(0.0629)		
ADL_poorest20								0.0192	
								(0.0703)	
ADL_nopoorest20								0.137***	
								(0.0391)	
ADL_HAQhigh									0.115
									(0.0855)
ADL_noHAQhigh									0.106***
									(0.0372)
Observations	1,822	1,822	1,822	5,775	5,775	5,775	2,704	2,704	2,704
Number of id	1,702	1,702	1,702	5,053	5,053	5,053	2,548	2,548	2,548

Notes: Column (1) to (3) are based on the constructed dataset using *new_severe* as the treatment, column (4) to (6) using *new_moderate* and column (7) to (9) using *deteriorationADL*. The dependent variable of each estimation is the logarithm of OOP medical expenditure. All provincial and wave dummies are included in each estimation. Other control variables include all variables listed and defined in Table 3.1. The sample size is much smaller than that of previous tables because only treated and matched observations are kept.

Appendix 3.1 Consumption compositions

Variable	Variable code in CHARLS	Description
foodin	[GE006]	Food at home expenditure
medicalexp	[GE010_6]	Household total direct and indirect OOP medical expenditure
nondurable	[GE006]	Food at home expenditure
	[GE007]	Expenditure on eating out
	[GE008]	Expenditure on alcohol, cigarettes, cigars and tobacco
	[GE009_1]	Communication fees including postage, internet telephone and mobile bills
	[GE009_2]	Utilities (water and electricity)
	[GE009_3]	Fuels (gas and coal)
	[GE009_4]	Hiring housekeepers and servants
	[GE009_5]	Local commuting
	[GE009_6]	Household items
	[GE009_7]	Books, newspapers, CDs and magazines
	[GE010_1]	Clothing
	[GE010_2]	Trips and vocations
	[GE010_3]	Heating
	[GE010_5]	Education and training
	[GE010_6]	Total direct and indirect OOP medical expenditure
	[GE010_7]	Fitness
	[GE010_8]	Personal care products
	[GE010_11]	Property management fees
	[GE010_12]	Taxes and fees payable to government
	[GE010_13]	Donations

Notes: ***nonmed***= ***nondurable*** – ***medicalexp***
nonfoodmed =***nonmed*** – ***foodin***
Source: The 2011, 2013 and 2015 CHARLS

Appendix 3.2 A list of ADLs in CHARLS

Code	Difficulty of …
[DB001]	Running or jogging 1km
[DB002]	Walking 1km
[DB003]	Walking 100m
[DB004]	Getting up from a chair after sitting for a long period
[DB005]	Climbing several flights of stairs without resting
[DB006]	Stooping, kneeling or crouching
[DB007]	Reaching or extending your arms above shoulder level
[DB008]	Lifting or carrying weights over 5kg
[DB009]	Picking up a small coin from a table
[DB0010]	Dressing
[DB0011]	Bathing or showering
[DB0012]	Eating
[DB0013]	Getting out of bed
[DB0014]	Using toilet
[DB0015]	Controlling urination and defecation
[DB0016]	Doing household chores
[DB0017]	Cooking
[DB0018]	Shopping for grocery
[DB0019]	Managing money
[DB0020]	Taking medication

Source: The 2011, 2013 and 2015 CHARLS.

Appendix 3.3 Tests for covariate balance after propensity score matching

	Mean			t-test	
	Treated	Control	%bias	t	P-value
agesq	3996.6	4012.7	-1.4	-0.3	0.761
hhsizesq	12.233	12.177	0.4	0.1	0.921
incomesq	8.5136	8.1391	5.4	1.19	0.235
wealthsq	3.7305	3.4715	4	0.91	0.363
lhhitot	2.5863	2.5155	5.2	1.15	0.249
lhhfinassets	1.2829	1.2084	5.1	1.14	0.254
age	62.562	62.701	-1.5	-0.33	0.738
male	0.43555	0.4158	4	0.88	0.381
married	0.81809	0.81601	0.5	0.12	0.906
widowed	0.12058	0.11123	3	0.64	0.522
illiterate	0.27963	0.30146	-4.9	-1.05	0.292
highschool	0.10603	0.09252	4.4	0.99	0.322
highedu	0.03119	0.02703	2.6	0.54	0.588
hhsize	3.1206	3.0998	1.3	0.29	0.775
stillworking	0.55301	0.5738	-4.3	-0.92	0.358
homeowner	0.86383	0.85863	1.6	0.33	0.742
goodhealth	0.0738	0.06341	3	0.9	0.367
poorhealth	0.50208	0.50936	-1.6	-0.32	0.75
depressed	0.40644	0.43763	-6.5	-1.38	0.166
noinpatientcare	0.64345	0.65177	-2	-0.38	0.703
mt1inpatientcare	0.14969	0.12994	6.9	1.25	0.212
noinsurance	0.0104	0.00936	0.9	0.23	0.818
Mean bias 3.2	**Rubin's B**	**15.1**			
Median bias 3.0	**Rubin's R**	**0.99**			

Notes: The quality of matching is tested using Stata 15 command pstest. %bias is the % difference of the sample means in the treated and matched groups as a percentage of the square root of the average of the sample variances in the treated and matched groups. Mean and median bias are the mean and median of the distribution of bias. T-tests are conducted for comparing the mean differences between the treated and matched groups after matching. Rubin (2001) recommends B less and 25 and R between 0.5 and 2 for the samples to sufficiently balanced.

Appendix 3.3 Continued

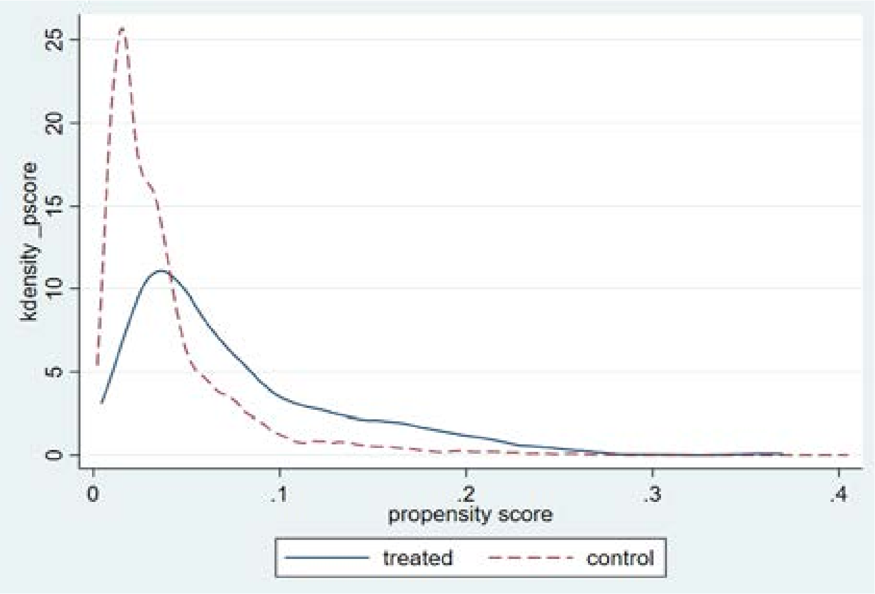

Figure 3.3 a The estimated propensity score before matching

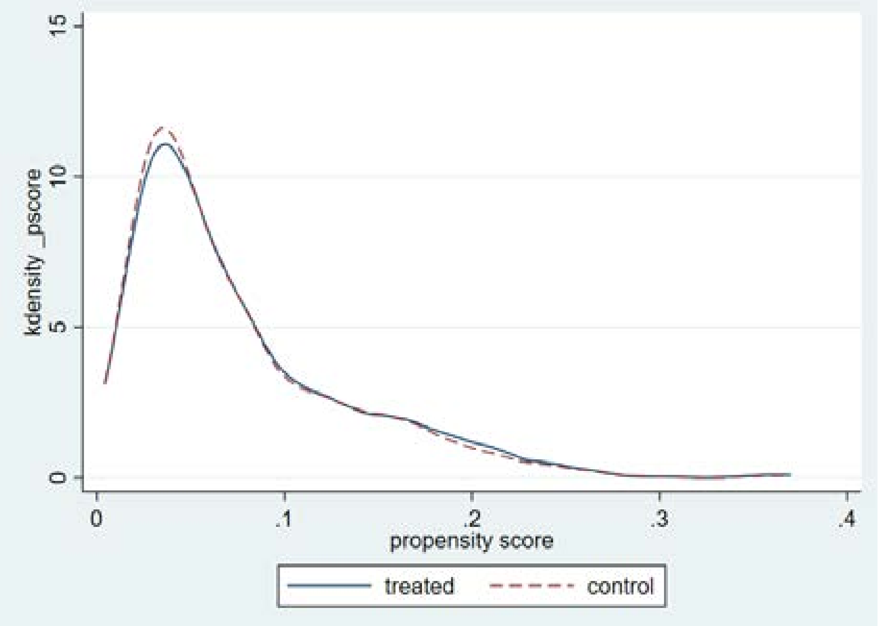

Figure 3.3 b The estimated propensity score after matching

Chapter Four: Financial Stress and Body Weight: An Empirical Investigation among European Older Adults

4.1. Introduction

Two clear trends have been observed in Europe over the past decades. On the one hand, European household debt has risen rapidly in many countries (Guiso and Sodini, 2013). The increasing availability of credit cards, loans and credit purchases as a result of consumption boosting policies, as well as the relaxed credit constraints after the global financial crisis have led to a massive explosion of household debt.

According to OECD Statistics (2016), household debt, measured as a percentage of net disposable income ratio ranged from 47.5 (Lithuania) to 285.8 (Demark). The average among the EU 28 countries is 121.5. The debt-income ratio of Demark, the Netherlands, Luxembourg, Sweden, Ireland, the United Kingdom, Portugal, Finland, Spain, and Belgium is above the EU average. With easier access to credit, many EU citizens are struggling to repay their debts and thus face substantial financial difficulties. According to European Union Statistics on Income and Living Conditions (EU-SILC) Survey, in 2015, nearly 30 percent of surveyed individuals reported they felt the repayment of debts from hire purchases or loans as a financial burden; and 43 percent of them reported financial burden due to housing costs. Moreover, almost one in eight of them (12.6 percent) were in arrears on mortgage or rent payments, and/or hire-purchase/loan agreements due to financial difficulties in the last 12 months.

On the other hand, the prevalence of obesity has more than doubled in the WHO European Regions since 1980 (WHO, 2014). According to the latest WHO estimation, obesity (Body Mass Index (BMI) $\geq$ 30) affects 20-30 percent of adults in European Regions, and overweight

(BMI $\geq$ 25) affects 45-70 percent of them[47]. Obesity has been recognised as one of the greatest public health challenges of the 21st century in the western world. Apart from causing physical disabilities and psychological problems, excess weight contributes to a higher risk of developing cardiovascular diseases, cancer and diabetes. In addition to reducing personal well-being, the public cost of obesity is extremely high. In 2012, obesity was estimated to be responsible for €81 billion direct and indirect medical costs, which is equivalent to 7 percent of the total health expenditure in the EU. If no action is taken, the magnitude of these obesity-related costs is likely to continue rising over time and latent effects, such as possible genetic changes, may occur in the next and subsequent generations (Hunt and Ferguson, 2014).

Although it is well recognised that weight gain results from caloric imbalances where calories consumed are higher than calories used, it remains unclear what are the factors causing this imbalance and ultimately leading to the prevalence of obesity. Genetic factors have been found correlated to the occurrence of obesity since obesity tends to concentrate within a family. Specifically, the risk of being obese is two to eight times higher for a person with a family history of obesity compared to a person without (Centers for Disease Control and Prevention, 2018). Yet, these findings have rather limited power to explain the increasing prevalence of obesity over the past decades since generically human beings have not changed dramatically during this period.

More recently, the focus of obesity-related studies has been shifted to socioeconomic factors, which have been argued to be major determinants of obesity, as food consumption and body weight are both economic decisions in the end (Ruhm, 2012). Consumers balance the utility gain from food consumption against the utility loss from future weight gains as well as

[47] Source: http://www.euro.who.int/en/health-topics/noncommunicable-diseases/obesity/data-and-statistics. Body Mass Index (BMI) is defined as weight (kg)/height (m)^2. It is the most widely used body weight indicator in literature and practice.

from potential health risks. In the literature, various socioeconomic factors have been related to obesity, such as race, ethnicity, age, income, education and employment status (Rashad, 2006, Villar and Quintana-Domeque, 2009, von Hippel and Lynch, 2014, Webbink et al., 2010) However, to the best of my knowledge, only very little attention has been paid to financial difficulties, a direct consequence of the credit expansion in the modern economy.

Worsening financial circumstances have been found to be associated with deteriorating mental and physical health for individuals (Bridges and Disney, 2010, Selenko and Batinic, 2011, Sweet et al., 2013, Keese and Schmitz, 2014). However, evidence of a possible correlation between financial health and body weight is not well-established in the literature. Intuitively, on the one hand, individuals living with ongoing financial difficulties are more vulnerable to chronic stress. Evidence has shown chronic life stress (long-term stress) is causally linked to possible weight gain (Kandiah et al., 2006, Torres and Nowson, 2007). In addition, in laboratorial studies, a positive association between chronic stress and energy-dense food intake has been confirmed (Rowland and Antelman, 1976, Dallman et al., 2003). When exposed to chronic stress, people tend to eat comfort food containing high fat or carbohydrate caloric content to lower the activities of the stress-response network in the brain. Thus, it seems reasonable to propose a link between financial stress and weight gain. In the presence of financial difficulties, which are common stressors in modern society, stress-induced eating may result in an increased intake of calories, and ultimately in a higher prevalence of obesity.

On the other hand, financial difficulties such as over-indebtedness may be a consequence of having a high time preference rate, which has been found to be correlated with a higher body weight (Smith et al., 2005, Zhang and Rashad, 2008). Time preference is the rate at which people are willing to trade current utility for future benefit (Smith et al., 2005). Individuals with a higher time preference rate generally value the present more than the future. Thus, they are more likely to enjoy all the gratifications in the present and save less for the future compared to others with lower time preference rates. Intuitively, when borrowing is available, those with higher rates of time preference are more likely to take debts to increase consumption in the current period, *ceteris paribus*. Moreover, since individuals with high rates of time preference discount the future more compared to those with lower rates, they are less likely to be active in exercises because the health benefit of exercising is usually delivered in the future. For the same reasons, they are also more likely to over-eat in the present, which may lead to a higher chance of gaining weight.

This paper investigates the extent to which financial difficulties and body weight are correlated in European countries. Recalling the fact that 43 percent individuals reported having financial burdens in the EU-SILC survey, I question if financial stress can partially explain the high prevalence of obesity observed in European countries nowadays. To this end, I make use of a cross-nationally comparable and representative panel dataset, the Survey of Health, Ageing and Retirement in Europe (SHARE) over the period 2004 to 2015. By applying a dynamic analysis framework and controlling for a comprehensive set of confounders, I find a high level of state dependence of body weight status in all sampled countries[48]. This suggests a necessity of taking the state dependence of body weight into consideration. In addition, I find little evidence of a positive link between financial stress and body weight, with such a link is being found only in Austria, Germany, Sweden, Spain, France, Italy and Switzerland. This link is generally robust to using corrected self-reported weight measures, as well as different financial stress measures.

[48] These are Austria, Germany, Sweden, Spain, Italy, France, Denmark, Switzerland and Belgium. All sample selection criteria are illustrated in Section 4.3.

In the context of an increasing prevalence of obesity and overweight, this study sheds new light on reasons for this epidemic in European countries. It also contributes to the existing literature in the following ways.

First, I conduct a comparative study across nine European countries by utilising the representative, cross-nationally comparable, and recent SHARE dataset. To the best of my knowledge, none of the existing studies analyse the finance-health nexus in a country-specific comparative setting. Second, I specifically estimate the relationship between financial stress and body weight. Although a better understanding of possible body weight responses to financial stress is of great importance in the context of the recent global financial crisis and the increasing prevalence of obesity, most of existing studies on financial stress focus on mental health-related outcomes. Third, I take into account the state dependence of obesity. There is a strong persistence in one's body weight. An individual who is obese in the past is likely to remain obese in the future (in the absence of dramatic changes of behaviours or health status). However, only few studies in the literature, have treated obesity in a dynamic setting. Fourth, I also consider the initial condition of one's body weight status at the beginning of the sampled period. If body weight is persistent over time, ignoring the initial condition may lead to an overestimation of the true state dependence of obesity. To the best of my knowledge, no study in the literature has taken into account the initial condition of obesity.

The remainder of this paper is organised as follows. Section 4.2 provides a comprehensive literature review. Section 4.3 describes the data and descriptive statistics. Section 4.4 illustrates the econometric specifications. Section 4.5 presents and discusses the empirical results. Section 4.6 provides robustness checks. Section 4.7 discusses possible policy implications and limitations of this study. Section 4.8 concludes.

4.2. Literature review

The literature review is divided into two parts: I firstly review papers discussing existing empirical evidence on the relationship between various measures of socioeconomic status (SES) and body weight[49]. I then provide a selective review of studies looking at time preferences, financial circumstances and their impact on body weight.

4.2.1. SES and obesity

The relationship between SES and an individuals' body weight has long been discussed in the literature. Socioeconomic status is a complex combination of one's social and economic situation in relation to others. Income and education level are widely used to represent one's SES. In the literature, SES has been found to be closely associated to body weight.

Rashad (2006) estimates the possible determinants of BMI using confidential micro-level data from the First, Second, and Third National Health and Nutrition Examination Surveys (NHANES I, II, and III, respectively), which consist of a pooled sample of 28,696 individuals from the US [50]. After controlling for caloric intake and physical activity level, she finds that having a college degree and higher household income are in general associated with a lower BMI in women.

---

[49] A number of studies have shown that macroeconomic factors, such as food prices and the prevalence of restaurants (Cutler et al., 2003, Chou et al., 2004, Drewnowski and Darmon, 2005), cigarette prices and taxes (Gruber and Frakes, 2006, Baum, 2009), technology advancement (Finkelstein et al., 2005, Lakdawalla and Philipson, 2009), and urbanisations (Eid et al., 2008, Baum and Chou, 2011) are associated with the prevalence of obesity. I limit this discussion to studies attributing the prevalence of obesity to variations in socioeconomic status at the micro level.

[50] NHANES I was conducted between 1971 and 1975 by the National Centre for Health Statistics, US; NHANES II, between 1976 and 1980; NHANES III, between 1988 and 1994.

Villar and Quintana-Domeque (2009) conduct a similar study in Europe using the 1994-2001 European Community Household Panel. They find a negative association between income and BMI in women, but not in men, and this negative association increases over the BMI distribution. They attribute the mixed results to biases including measurement errors in self-reported weight and income, omitted variables that affect both income and BMI, and reverse causality. In addition, they argue that different results between men and women may be driven by the wage penalty for women in the labour market, whereby obese women are penalised with lower wages.

Ljungvall and Gerdtham (2010) study income-related inequalities in obesity using a Swedish longitudinal dataset taken from the Swedish Survey of Living Conditions (1980 to 1997, three waves in total). They find obesity is less common in women with relative higher income. Furthermore, the difference in obesity among different income groups decreases with age. The authors argue that the decreasing difference in obesity among Swedish women is due to the increasing prevalence of obesity in all age groups.

As for the education level, there exists more consensus in the literature. Better educated individuals have been found to have a lower BMI and are less likely to be overweight/obese. This link can be explained by *selection* (von Hippel and Lynch, 2014, Benson et al., 2017): those with lower BMI are more likely to complete higher levels of education compared to those with higher BMI; or *causation* (Webbink et al., 2010): higher education is associated with advantages such as a higher income and better knowledge of the importance of keeping fit which help maintain a healthy weight.

Using data from the 1997 National Longitudinal Survey of Youth (NLSY97) which tracks body weight in a sample of individuals aged 15 to 29, von Hippel and Lynch (2014) favour the *selection* explanation. They find male adolescents who are overweight/obese have 16 percent/31 percent lower likelihood of completing higher education. The corresponding percentages for female adolescents are 47 percent and 60 percent, respectively. The authors conclude that the association between body weight and education is mainly due to *selection* rather than *causation* because only 25 percent of the body weight gradient can be explained by higher education attainment. However, the causal effect of education could increase for respondents older than 29. Hence, later, Benson et al. (2017) use the NLSY79 which covers older respondents compared to the NLSY97 and apply the same analytical framework as von Hippel and Lynch (2014). They confirm the findings from von Hippel and Lynch (2014). Specifically, at age 48, most of the negative association between body weight and education is found to be due to *selection* rather than *causation*[51].

Using longitudinal data from the Australian Twin Register, which consists of 5,967 adult twin pairs, Webbink et al. (2010) attempt to identify *causation* by utilising the within-twin estimator. They argue that the within-twin estimator controls for all unobserved genetic and family factors between a pair of twins. They find that education reduces the probability of being overweight within pairs of twins in men but not women. However, although twins share many genetic and socioeconomic commons, they are not identical. The differences are especially prevalent towards their late adulthood when each twin within a pair leaves the family and may acquire a different SES. The results may therefore still be affected by individual-specific heterogeneities. In addition, the results might be biased if unobserved family factors affect both education and body weight.

[51] The NLSY79 is made up of individuals born between 1956 and 1964. This sample is followed up until 2012, when this study is conducted. In 2012, the NLSY79 participants were aged 48 to 56. von Hippel and Lynch (2014) restrict their sample to NLSY79 participants who were aged 17-18 in 1979 and 48-49 in 2012.

These studies suggest the need for investigating the effects of alternative SES measures other than income and education on body weight, as neither income nor education have a consistently large impact on body weight. To address this issue, by applying gene-environment interaction analyses to the Health and Retirement Study (HRS) genetic sample, Liu and Guo (2015) find that persistent low SES over the life course, or moving from high SES to low SES enlarges the effect of genetic influence on BMI. In contrast, persistent high SES or moving from low SES to high SES over the life course compensates for this effect. Liu and Guo (2015) measure childhood SES by father's occupation. The SES of young adults is measured as years of education, and that of middle/late adults as total household wealth. Their finding suggests a link between individual's SES and BMI after controlling for the genetic differences.

As for SES factors other than income and education, Godard (2016) estimates the effect of retirement on BMI, as well as on the probability of being overweight/obese of the older population in Europe using the 2004, 2006 and 2010-2011 waves of SHARE. Her results show men retiring from strenuous jobs have a higher probability of being obese/overweight. Yet, the same pattern does not apply to women. In addition, the state dependence of body weight is confirmed in this study. This finding indicates the importance of considering the dynamics of weight in relevant studies.

In a nutshell, findings on income are mixed. Empirical studies find a negative association between body weight and income in women only (Rashad, 2006, Villar and Quintana-Domeque, 2009, Ljungvall and Gerdtham, 2010, Baum and Chou, 2011), as well as in both men and women (Salmasi and Celidoni, 2017). Higher education has been found to be consistently linked to lower weight (von Hippel and Lynch, 2014, Cutler and Lleras-Muney, 2010, Ogden et al., 2010, Benson et al., 2017), although the direction of this association is controversial. In other words, it is unclear if a lack of education causes higher body weight or *vice versa*.

4.2.2. Financial circumstances, time preferences and obesity

Financial circumstances are closely associated, but not interchangeable, with socioeconomic status (SES). Therefore, they deserves specific attention compared to conventional SES such as income, education, housing tenure and social class (Conklin et al., 2013). There is a strand of literature studying the effect of financial situation on obesity. In addition, since financial situation could be a reflection of one's time preference[52], I also include studies look at the impact of time preferences on body weight in this literature review. These studies are mainly conducted on the US (Adams and Moore, 2007, Averett and Smith, 2014, Courtemanche et al., 2015, Komlos et al., 2004, Smith et al., 2005), Australia (Siahpush et al., 2014, Rohde et al., 2017), or Japan (Ikeda et al., 2010, Kang and Ikeda, 2016). To the best of my knowledge, in European countries, empirical evidence is only available for the Netherlands (Webley and Nyhus, 2001, Borghans and Golsteyn, 2006), Germany (Münster et al., 2009, Keese and Schmitz, 2014), Switzerland (Guerra et al., 2015), and the UK (Guariglia et al., 2018, Pickering et al., 2017, Conklin et al., 2013). Furthermore, there are no cross-country comparative studies available.

4.2.2.1. Financial circumstances and health

In the context of recovering from the 2008 financial crisis and the following sovereign debt crisis, individuals were found to struggle with financial difficulties in developed countries (Prentice et al., 2017). However, existing studies on financial stress largely focus on its effects on psychological health, while its possible effects on body weight are rarely mentioned[53].

[52] Many studies have used individuals' indebtedness as measure of their time preference rates. See, for example, Guariglia et al. (2018) and Pickering et al. (2017).

[53] Richardson et al. (2013) conducted a comprehensive review of studies on the relationship between personal unsecured debt and mental and physical health. 65 papers are included in the review but only 5 of them look at the effect of debt on body weight as one of the health outcomes.

Empirical evidence suggests that financial difficulties, a very common stressor in modern society, are associated with high stress and depression (Bridges and Disney, 2010, Selenko and Batinic, 2011, Hojman et al., 2016, Koltai et al., 2018), as well as with a worse general health status (Drentea and Lavrakas, 2000, Sweet et al., 2013, Keese and Schmitz, 2014, Clayton et al., 2015). As for the effect of financial circumstances on body weight, conditioning on a set of other socio-economic and demographic factors, a few empirical studies provide evidence of an association between financial hardship and weight gain or higher likelihood of being overweight/obese (Guariglia et al., 2018, Münster et al., 2009, Siahpush et al., 2014, Averett and Smith, 2014, Rohde et al., 2017).

Bridges and Disney (2010) examine the effect of household indebtedness on depression using data from the UK's Families and Children Survey for the period 1999-2005. They find a strong correlation between subjective self-reported financial difficulties and depression, while the link is much weaker for objective financial difficulties. They argue that the effect of objective financial difficulties on depression is mediated by individuals' self-perception of financial difficulties which result from individual-specific heterogeneity.

Selenko and Batinic (2011) contact 106 clients of an Austrian debt-counselling institution who were in the process of filing for bankruptcy and examine their mental health status by using a 12-item mental health related questionnaire. They find that individuals who perceive financial difficulties in the present have significantly worse mental health scores compared to others. The actual amount of debt is, surprisingly, neither correlated with perceived financial strain nor the mental health score. This suggests once more that there is a clear distinction between objective and subject financial stress relating to debt. It is the self-perceived financial situation, rather than the objective amount of debt, that affects one's mental health. However, since this study is based on a rather small sample, the findings may not be representative.

Clayton et al. (2015) investigate the debt-health relationship at the aggregate level. Using country-level data covering 17 European countries over the period 1995 to 2012, they find that long-term debts are associated with poor health outcomes, while short- and medium-term debts are positively related to health outcomes. However, this study is limited to country-level data, and the measures of health outcome indicators are fairly simple, namely life expectancy and mortality. In addition, no heterogeneities across sample countries are discussed.

Using data from waves 1 (1994/1995), 3 (2002/2003), and 4 (2007/2008) of the National Longitudinal Study of Adolescent Health (Add Health), Sweet et al. (2013) find a higher financial debt-to-asset ratio to be associated with higher levels of perceived stress and depression, worse self-reported general health, and higher diastolic blood pressure. Their findings provide evidence for the impacts of debt on both physical and mental health. However, since the financial debt-related information is only available in Add Health wave 4, their econometric analysis is performed at a cross-sectional level. This raises the concern that the results may be driven by reverse causality or individual heterogeneity.

Hojman et al. (2016) study the relationship between household debt and mental health status using a large dataset consisting of 10,900 Chilean households from 2002 to 2009. They find that those with persistent over-indebtedness have higher depressive symptoms. They also find households who transited from high indebtedness to moderate indebtedness have no additional depressive symptoms compared to those who have been in moderate indebtedness for the whole data period. Household debt trajectories between different indebtedness statuses are calculated between 2006 and 2009. However, since most debts considered are consumer debts which normally have less than 1-year maturity, it is possible that households classified as never in debt in fact had debts but paid them off between the two survey interviews. Thus, the debt-depression link highlighted in this paper may be biased.

Using three waves (conducted in 2011, 2013, and 2015 respectively) of the Canadian Work, Stress, and Health Study, Koltai et al. (2018) also find a poorer financial situation to be linked to poorer mental health. Moreover, they state mastery, a psychological force that stimulates an individual to solve problems individually[54], weakens this association. Time invariant unobservables are taken into account, but the utilisation of fixed-effects models rules out the possibility of studying the effects of persistent financial strain and low income on health outcomes because households without any changes in financial situation are automatically excluded from the analysis.

Overall, these empirical studies consistently show that financial hardships are associated with poorer mental and physical health[55]. However, as for the effect of financial difficulties on body weight, the literature lacks consensus.

By analysing data from the National College Health Assessment (2002-2003), Adams and Moore (2007) find a positive association between high risk credit debt and BMI in US college students aged 18 to 25. However, their analysis' frame is only cross-sectional. The results are likely to be biased by not accounting for individual heterogeneity. In addition, being at the early stage of the life-cycle, college students aged 18 to 25 may not yet have accumulated enough debt for a full effect of debt burden on health to be detected.

Münster et al. (2009) assess the association between indebtedness and obesity using a cross-sectional dataset including 949 over-indebted clients of debt counselling centres in Germany in 2006-2007. They observe a higher prevalence of overweight/obesity among over-

[54] Koltai et al. (2018) do not give clear definition of mastery. The definition here is found in Morgan et al. (1990).

[55] I summarise studies on the impact of financial difficulties on physical/mental health because health, especially mental health status, is arguably the mediator explaining the finance-weight link.

indebted individuals after controlling for other confounders such as age, gender, education, income and mental health status. However, no causality can be identified from this study because of the cross-sectional data structure.

Using the US Add Health, a school based longitudinal study conducted between 1994 and 1995 when the interviewees were aged 11-21, and between 2001 and 2002, when they were aged 18-28, Averett and Smith (2014) find a positive relationship between having trouble paying bills and being overweight/obese in women. Yet, the data they use is conducted almost two decades ago when the prevalence of obesity was not a global epidemic. In addition, as the maximum age of their subjects is only 28, the prevalence of financial debt might be underestimated as younger adults are less likely to have major debts compared to their older counterparts.

Siahpush et al. (2014) estimate the association between financial stress and obesity in Australia. Using data from the Household Income and Labour Dynamic in Australia (HILDA), they find the risk of being obese in 2010 is 20 percent higher for individuals who experienced financial stress in both 2008 and 2009, compared to those who did not experience financial stress in either year. Yet, other factors that are likely to affect both financial situation and body weight are not considered in this study, and individuals' unobserved heterogeneity is not taken into account. The estimation is thus likely to be biased.

Keese and Schmitz (2014) study the relationship between household indebtedness and different health outcomes such as health satisfaction, mental health and obesity in Germany from 1999 to 2009. The fixed-effects setting enables them to control for time-invariant unobservable heterogeneity. They find significant negative associations between indebtedness and health satisfaction, as well as mental health, but the same does not hold for obesity.

However, as the prevalence of both obesity and debts has increased dramatically in the past decades, a stronger correlation between indebtedness and obesity could appear if more recent datasets were used.

Using data from the Cohorte Lausannoise (CoLaus) Study, a population-based health-related study which was firstly conducted in Lausanne Switzerland between 2003 and 2006 and followed up between 2009 and 2012, Guerra et al. (2015) find that the financial difficulties indicated by receiving social help are associated with a more than five kilograms increase in body weight. They argue that diet quality changes following financial difficulties, which leads, in turn, to weight gain. Yet, the time gap between two waves of the CoLaus is problematic since the follow-up study is conducted almost 6 years after the first study. In such a long time span, body weight is very likely to be affected by many other factors such as physical/mental health status, that are not controlled for in the analysis. Also, it is hard to justify the argument that one's financial difficulties 6 years ago affect current body weight.

Conklin et al. (2013) analyse the effect of financial hardships on obesity focusing on older British people living in Norfolk, UK. They find that financial hardship defined as *having less than enough money for one's needs* is associated with a 1.1 (0.8) times higher probability of being obese in women (men) compared to those who reported *having more than enough money*. Financial hardship defined as always or often *not having enough money for food/clothing* is associated with a 0.4 and 0.8 times higher probability of being obese in women and men, respectively (compared to those who *never have this money shortage).* The strongest association is found when financial hardship is defined as *having difficulty paying bills*. Compared to those who do not have this difficulty, women and men with *difficulty paying bills* show a 1.2 and 1.4 times higher probability of being obese.

More recently, using the 2006 to 2011 HILDA survey and an OLS estimator, Rohde et al. (2017) find that those with economic insecurity are more likely to have a higher BMI in Australia. They also find the correlation to be stronger in individuals with higher BMI and/or with more economic insecurities using quantile regressions. However, their econometric analysis is only conducted at the cross-sectional level, and possible individual heterogeneity is not considered.

The closest-related study to ours is Guariglia et al. (2018). Instead of looking at financial stress, they find that the absence of financial debt or high savings are associated with a lower probability of being obese/overweight. To this end, they make use of the English Longitudinal Survey of Aging over the period 2002-2012. In addition to BMI, they also use waist circumference which is argued to be a better measure of adiposity compared to BMI. They find having no debt is strongly related to a lower chance of being overweight/obese, especially among women. It is worth mentioning that, to the best of my knowledge, this study is the only one in the literature which has controlled for state dependence as well as initial conditions of body weight status.

4.2.2.2. The role of time preferences

Another strand of literature studies the impact of time preferences on body weight, because ultimately an individual's financial situation could be a reflection of his/her time preference[56]. In addition, time preferences may affect body weight also through food consumption and exercise decisions. In the literature, time preferences are found to be significantly correlated with the chance of being overweight/obese. Individuals with a higher time preference rate

[56] The rate of time preference is the rate at which individuals are willing to trade current utility for future benefit. Individuals with a higher rate of time preference value the present more than the future in general, and therefore are less patient.

discount future consumption more, and, as such, are less patient and more interested in current consumption, compared to those with a lower rate. In developed countries, as both monetary and time costs of caloric intake are very low, individuals with a higher rate of time preference are more likely to consume more calories than others (Ikeda et al., 2010). In addition, since the benefits of exercising and keeping a balanced diet are more likely to happen in the future, people with a higher rate of time preference are less likely to over-eat and procrastinate exercises, leading to higher body weight.

At the aggregate level, Komlos et al. (2004) use the net domestic saving rate and debt-to-income ratio as two proxies of time preferences. The lower the savings and the higher the debt-to-income ratios are, the higher the time preference rates. They find a positive relationship between time preferences and obesity in the US. However, this conclusion is drawn in the absence of a micro-level econometric analyses, and without controlling for other confounders. Drawing data from the NLSY79 for the US, Smith et al. (2005) test the relationship between rate of time preference and BMI. In this study, saving indicates a low time preference rate and dissaving indicates a high time preference rate. They find that the rate of time preference and BMI are positively correlated among black and Hispanic men and black women. Their findings also suggest a positive association between the rate of time preference and the likelihood of being obese among black men.

Borghans and Golsteyn (2006) estimate the relationship between changes in the rate of time discounting rate and differences in body weight among Dutch individuals. To this end, they make use of a large dataset from the DNB Household Survey, which covers the period 1992-2004. By applying 25 proxies of individual time preferences covering risk attitude, future attitude, financial planning horizon, and values of savings, assets, and liabilities, they find that individuals with higher time-preference rates show higher BMI. Furthermore, this association is found to be more prevalent in women. However, not all time preference proxies are significantly associated with body weight. In another word, their findings are very sensitive to the selection of time preference proxy. Specifically, proxies of time preference rates related to the ability to manage expenditure are more closely correlated to BMI. Additionally, the state dependence of body weight is not considered in this study.

Using data taken from the Japan Household Survey on Consumer Preferences and Satisfaction 2005, Ikeda et al. (2010) study the impact of time preference on body weight. They document three aspects of time preference, namely impatience, hyperbolic discounting and the sign effect. Impatience represents a stronger preference for present consumption. Hyperbolic discounting implies agents having a high time discounting rate for very short horizons, while having a relatively lower rate for longer horizons. The sign effect implies agents discounting future gains at a higher rate than losses. The authors find that relative to their patient counterparts, individuals who are impatient show a higher BMI and a higher probability of being obese. Furthermore, procrastination, which is used as a measure of hyperbolic discounting is positively associated with BMI. Finally, individuals who do not show the sign effect are more likely to be obese. However, due to the cross-sectional nature of the dataset, the dynamics of body weight is not accounted for.

Courtemanche et al. (2015) utilise hypothetical intertemporal trade-off questions from the 2006 NLSY to calculate a series of discount factors which reflect respondents' impatience. They find impatience measured by higher discounting rates to be associated with higher BMI, as well as a higher probability of being overweight/obese. As the cost of obtaining food declined dramatically over the past decades, impatient consumers gained more weight compared to patient consumers because they responded more strongly to the falling prices. This finding may explain why increases in BMI have been concentrated in the right tail of the weight distribution. Finally, the authors also find that impatient consumers are more likely to respond to economic changes such as lowered food price compared to those who are patient.

Pickering et al. (2017) also investigate the relationship between time preference and body weight. Using data taken from six waves of the English Longitudinal Study of Ageing (ELSA) and adopting saving as a proxy for time preference, they find an unclear association between savings and the probability of being overweight/obese. Specifically, the decision to save is negatively associated with BMI, and placing savings in low risk investments is associated with a lower likelihood of being obese. Yet, these associations are not significant in all models. In addition, the authors do not observe any statistically significant association between the proportion of savings relative to total income and the probability of being overweight/obese.

4.2.3. Contributions to the literature

The majority of the above-mentioned studies have used cross-sectional data to study the links between financial stress/time preference and BMI/obesity/overweight. Associations from simple cross-sectional studies may be largely driven by unobservable individual heterogeneity and reverse causality. In addition, these studies have treated body weight as static and ignored the state dependence of obesity. This study aims at filling these gaps in the literature by applying a dynamic framework which considers the state dependence of body weight and controls for individuals' unobservables. Furthermore, my study compares, for the first time, the differences in impact of financial status on body weight across nine EU countries, focusing on older European individuals. This is particularly important in the context of population ageing and rising obesity in Europe.

4.3. Data and descriptive analysis

4.3.1. The Survey of Health, Ageing and Retirement in Europe (SHARE)

I use data from the SHARE, a harmonised, longitudinal cross-national panel database of micro data for more than 120,000 individuals aged 50 and above. Not only is the questionnaire ex-ante designed to be unified across participating countries, but also the data collection procedures are standardised. It thus provides truly comparable data, which enables comparative studies across surveyed European countries.

The SHARE consists of 6 waves over the period 2004 (wave 1) to 2015 (wave 6)[57]. It is conducted on a biennial basis. I exclude wave 3 (SHARELIFE) from the analysis because it only asks questions relating to respondents' life histories[58]. As it is a retrospective survey, information contained in wave 3 is highly different from that of other waves. It is also worth mentioning that, although the SHARE sample covers 21 European countries and Israel, I only keep countries which have participated in all waves in order to track the dynamics of obesity. After selection, my final sample consists of 9 countries, namely Austria, Germany, Sweden, Spain, Italy, France, Denmark, Switzerland, and Belgium. I form a balanced sample of respondents by including those who have participated in wave 1 and all subsequent waves (wave 3 is not considered) and provided non-missing information to all questions used to construct the regressors.

[57] Although wave 7 has been undertaken and its questionnaire are available online, only data for wave 1 to 6 have been released.
[58] Although I have excluded all observations in wave 3 from my analysis, I make use of some information from wave 3. To be specific, I identify respondents in later waves who have also participated in wave 3 and merge their historical information in wave 3 to other waves.

Table 4.1 presents the structure of the balanced panel dataset. The basic observation unit is individual-wave. The sample size for each country is above 2,000, with Austria and Switzerland as two exceptions. In SHARE, these two countries have the smallest baseline sample kept in the latest wave (wave 6) compared to other countries in the longitudinal setting[59]. Since I restrict the sample to respondents who have participated in all waves and reported non-missing information for all relevant questions, the final sample size is relatively small for these two countries.

It is also worth mentioning that extra care should be taken when interpreting results because the balanced sample may not be representative of the full sample. This is resulted from observations dropping out from subsequent surveys (*attrition*) and the refreshed sample not being included in my sample since I only track the baseline sample over time. However, as the main focus of this paper is accommodating the dynamics of body weight while taking individual heterogeneity into account, a balanced panel dataset which tracks the baseline sample over years is required. In addition, previous studies have shown that attrition of panel data has limited impact on econometric estimations. Behr et al. (2005) analyse the extent of panel attrition in the European Community Household Panel and find no evidence of substantial attrition biases. They also find that the ranking of countries in terms of household mover-stayer structure is not affected by attrition, which justifies comparative studies for European countries using survey datasets in the presence of attrition. Although their research question is not directly linked to ours, stayer-leaver analysis is supposed to be very sensitive to attrition because mover-stayer transitions reflect income changes and are further related to residential mobility and changes of household compositions. Evidence has shown that low income, residential mobility and

[59] For details of sample structure, please see http://www.share-project.org/data-documentation/sample.html

changes of household composition highly contribute to respondent drop-outs from a survey Behr et al. (2005). Hence, if the estimations for this topic show no sign of significant attrition biases, this alleviates the concerns for the presence of attrition in other comparative studies. Using the British Household Panel Survey and the European Community Household Panel, Jones et al. (2006) estimate the association between socioeconomic status and self-assessed health and test whether or not estimations results are sensitive to non-responses and attritions. This topic is more relevant to ours compared to Behr et al. (2005). They compare the estimations obtained from a balanced sample and an unbalanced panel with corrections for non-response and attrition by using inverse probability weights and find no major differences in the estimations of the variables of interest.

4.3.2. Body weight variables:

I use self-reported height and weight information to calculate the BMI of each individual. An individual is considered overweight if s/he has a BMI greater or equal to 25, and obese if his/her BMI is greater or equal to 30[60]. It has been argued that BMI is not a perfect measure of body fatness because it does not distinguish fat from fat-free mass such as weight of muscles and bones, especially for men (Burkhauser and Cawley, 2008). However, studies have shown that body fat mass increases and muscle mass decreases with age (St-Onge, 2005). Hence, BMI is justified as a valid indicator of weight at least for elderly people.

I am aware that self-reported weight is likely to be biased especially at the right-end of the weight distribution because individuals with higher weight have incentives to underreport

[60] My overweight sample also includes those who are obese. In the following text, overweight means both overweight and obese.

their weight. This may lead to a downward biased BMI and proportion of overweight/obese respondents in my sample.

To avoid these problems, I adjust the self-reported weight following Cawley et al. (2017) by using information from a validation dataset, the Health and Retirement Survey (HRS) which contains both self-reported and measured body weight. This enables me to estimate the relationship between self-reported and measured body weight controlling for other individual characteristics such as age and gender. I then check if my results are robust to estimated report errors of self-reported weight. In a nutshell, despite the increasing prevalence of obesity/overweight observed in the sample, the regression results based on the corrected weight are similar to the ones using self-reported weight to construct dependent variables. State dependence of body weight is confirmed, although the link between financial situation and likelihood of being obese/overweight is weaker in this case. More details about this method and corresponding results are discussed in Section 4.6.1.

4.3.3. Financial stress

In each wave of SHARE, respondents are asked: "*Thinking of your household's total monthly income, would you say that your household is able to make ends meet?*" The answers to this question are "*with great difficulty/ with some difficulty/ fairly easily/ easily*". Those who answer "*with great difficulty*" or "*with some difficulty*" are defined as experiencing financial stress. I construct a dummy variable *finstress* equal to 1 in this case, and 0 otherwise.

One may argue that financial indebtedness could be a better measure of financial stress. However, in SHARE, one of the inconsistencies in terms of household debt between waves 1 and 2, on the one hand, and waves 4, 5, and 6, on the other is that the total amount of household debt is calculated including mortgages in the first two waves, but not in the latter. Also, bearing mortgages is considered as possessing financial debt in wave 1 and 2, but not in wave 4, 5, and 6. Thus, I cannot separate mortgages from other financial debts in the first two waves. Moreover, the amount of debt does not necessarily reflect financial hardship because wealthy households may have higher debt compared to others, without necessarily experiencing financial hardship. In addition, those with higher financial literacy may carry more debts than others simply because they have a higher demand for debts. By contrast, "*having great/some difficulty*" to make monthly ends qualifies as a direct reflection of households' real financial situation. However, considering that the amount of financial debt is a widely used indicator of financial stress, I have tested the effects of having high financial debt on body weight as a robustness check. More details are discussed in Section 4.6.2.

In line with other similar studies (Guariglia et al., 2018, Rohde et al., 2017, Pickering et al., 2017), I control for individuals' demographics (age, gender, marital status), education level measured as years of education attainment, retirement status, household size, risky behaviours (smoking and being physical inactive), self-perceived health status, mental health status measured as the standard EURO-D 12 items depression scale, whether or not one's daily activities are limited because of health issues, food consumption per capita in the household, as well as the value of household real assets and total household income. A set of wave dummies are included in all models to control the general time effect. Table 4.2 provides a summary description of all variable definitions, their sample means and standard deviations. It is worth noting that continues variables, namely food consumption per capital (*foodpc*), household real assets (*hrass*), household total annual income (*thinc*) and the body mass index (*BMI*) are winsorised at the bottom 1 percent and top 1 percent to address concern of outliers.

In Table 4.2, the mean of BMI is 26.68, which is higher than the overweight benchmark, indicating the prevalence of overweight in my sample. 20 percent of the respondents are obese and 62 percent of them are overweight or obese. 29 percent of the respondents are experiencing financial stress. 60 percent of the individuals are retired, 57 percent are female. The average education attainment among all respondents is 10.67 years. The average household real assets and total income are 247,400 and 38,400 Euro (2010 price level), respectively. 77 percent are home owners. 69 percent of the respondents have reported a good/very good/excellent self-perceived health status whilst 7 percent have rated their health status as poor.

Table 4.3 presents the differences in weight variables between financial stressed and non-stressed groups. In general, the difference in body weight between the stressed and non-stressed groups are found for all countries. Over 50 percent of the observations in Spain and Italy experience financial stress. The proportion of financially stressed observations is in the range of 19 percent to 30 percent in Austria, Germany, France and Belgium. Sweden, Denmark and Switzerland have significantly lower proportion of financially stressed observations compared to other countries. These statistics are highly consistent with the EU-SILC where the proportion of households not able to make monthly ends meet is the highest in Southern European countries and lowest in Nordic countries.

As for body weight, Spain has the highest prevalence of obesity (27.3 percent) and overweight (73.2 percent), while Switzerland has the lowest (12.0 percent and 51.1 percent respectively). For the rest of the countries, the occurrence of obesity is between 15.8 percent (Denmark) to 26.3 percent (Austria), and that of overweight is between 55.2 percent (Denmark) to 66.0 percent (Austria). These statistics show that over half of the observations in my sample are overweight regardless of country differences, indicating a high prevalence of overweight in the sampled countries. It is also worth mentioning that the mean of BMI for all countries is higher than 25, the benchmark for identifying overweight for adults.

The statistics also show great differences in weight variables between the financially stressed and non-stressed groups. The differences are highly statistically significant. In general, financially stressed observations are more likely to be obese/overweight and have a higher BMI. The difference between the stressed and non-stressed groups is considerably large in Germany. 74.5 percent (27.8 percent) of the financially stressed observations in Germany are overweight (obese), while 59.9 percent (16.5 percent) of other observations are overweight and obese. Austria and Switzerland display insignificant difference between the two groups in terms of the percentage of being overweight. In addition, the percentage difference of being obese between the financially stressed and non-stressed groups tends to be higher than that of overweight for most of the countries in my sample. This may indicate financial stress is more likely to affect the occurrence of obesity other than that of overweight.

4.4. Econometric approach

4.4.1. The dynamics of obesity

I firstly estimate the determinants of overweight/obesity allowing for state dependence of body weight and individual unobservables. To this end, I follow Wooldridge (2005) and Hernández-Quevedo et al. (2008). To be specific, I estimate the probability of an individual being overweight/obese ($w_{jit} = 1$) using a dynamic random-effects (RE) probit model of the form:

$$w_{j,i,t}^{*} = \alpha_j w_{j,i,t-1} + \beta_j^1 Ffs_{j,i,t} + \boldsymbol{\beta_j^2 X_{j,i,t}} + \boldsymbol{\gamma_j Z_{j,i}} + \delta_{j,i} + \varepsilon_{j,i,t},$$
$$j = 1,2; i = 1,2, \ldots, N; t = 2, \ldots, T \tag{4.1}$$

where $w_{j,i,t}^{*}$ is the latent likelihood of individual *i* being obese or overweight at time *t*. Subscript *j* denotes whether the equation is for dependent variable *obesity* or *overweight*. $w_{j,i,t-1}$ is the lagged value of the weight variable for individual i. $fs_{j,i,t}$ is the financial situation of individual *i* at wave *t*. $\boldsymbol{X_{jit}}$ is a vector of time-varying control variables and $\boldsymbol{Z_{ji}}$ is a vector of time-constant control variables. δ_{ji} denotes the individual-specific error term and ε_{jit} represents an idiosyncratic error component that is standard normally distributed. $w_{j,i,t}^{*}$ is not directly observable. Instead, we only observe whether or not individual *i* is overweight/obese. The relationship is defined as:

$$w_{j,i,t} = \begin{cases} 1 & if\ w_{j,i,t}^{*} > 0 \\ 0 & otherwise \end{cases} \tag{4.2}$$

The lagged value of the weight variable $w_{j,i,t-1}$ is included to control for the state dependence of weight since current weight highly depends on past weight. Using the NLSY79 (1985-2010), Daouli et al. (2014) document that 68.4 percent of the respondents who are obese in the baseline wave remain obese in the following wave, 42.3 percent remain obese after five waves, and about 35.1 percent after nine waves. 29.0 percent of the baseline respondents remain obese throughout all waves. Their finding highlights the importance of treating obesity as a dynamic matter. Moreover, the inclusion of past weight also reduces the concern of past weight affecting the current financial situation and other SES (Hernández-Quevedo et al., 2008).

In Equation 4.1, the presence of $\delta_{j,i}$ makes the composite error term $\delta_{j,i} + \varepsilon_{j,i,t}$ correlated over time. Moreover, to obtain consistent estimators, independence between the initial value of the outcome and $\delta_{j,i}$ is required. However, this assumption is too strong even if we could observe the whole process of $w_{j,i,t}$ (Wooldridge, 2005). For example, it is very unlikely that unobserved individual-specific genetic factors are not associated with the individual's initial weight at all, not to mention that the first weight observation in my sample is clearly not the true initial weight. In addition, $\delta_{j,i}$ may be correlated with some of the regressors in the model. To reduce these concerns, following Hernández-Quevedo et al. (2008), I model the distribution of the unobserved heterogeneity ($\delta_{j,i}$) conditional on the initial value of both the outcome and other time-varying variables in the form of:

$$\delta_{j,i} = \boldsymbol{\rho_j X_{j,i,1}} + \pi_j w_{j,i,1} + \mu_{j,i} \tag{4.3}$$

where $\boldsymbol{X_{j,i,1}}$ is a set of initial values of time-varying variables including the financial situation variable $finstress_{j,i,1}$, and $w_{j,i,1}$ is the initial obesity/overweight status for individual i. $\mu_{j,i}$ is assumed to be independent of all regressors as well as $\varepsilon_{j,i,t}$ for individual i at wave t. Thus, Equation 4.1 becomes:

$$w^*_{j,i,t} = \alpha_j w_{j,i,t-1} + \beta^1_j fs_{j,i,t} + \boldsymbol{\beta^2_j X_{j,i,t}} + \boldsymbol{\gamma_j Z_{j,i}} + \boldsymbol{\rho_j X_{j,i,1}} + \pi_j w_{j,i,1} + \mu_{j,i} + \varepsilon_{j,i,t}$$

$$j = 1,2; i = 1,2, \dots, N; t = 2, \dots, T \tag{4.4}$$

where $\alpha_j, \beta^1_j, \boldsymbol{\beta^2_j}, \boldsymbol{\gamma_j}, \boldsymbol{\rho_j}, \pi_j$ are parameters to be estimated. I estimate Equation 4.4 for each country separately. Selected results of estimating Equation 4.4 are presented in Table 4.4 and Table 4.5. Full results are presented in Appendix 4.1.

4.4.2. Quantile regression estimates

In addition to the dynamic RE Probit estimations, I also estimate a set of conditional quantile functions initially proposed by Koenker and Bassett Jr (1978) to accommodate the fact that the effects of the covariates may differ along the distribution of BMI. Quantile regression (QR) allows me to analyse such effects by estimating parameters conditional on a set of covariates for every quantile specified. This provides a more complete picture about the relationship between BMI and individuals' characteristics at different points in the distribution of BMI. The QR model is specified as follows:

$$Quant_\tau\left(BMI_{i,t} \middle| BMI_{i,t-1}, \boldsymbol{X_{i,t}}\right) = \alpha^\tau + \beta^\tau BMI_{i,t-1} + \boldsymbol{\gamma^\tau X_{i,t}} + \mu_i,\ i=1, \dots, N \tag{4.5}$$

where τ denotes the τth quantile of the distribution of BMI, and $0<\tau<1$. $Quant_\tau(\cdot)$ denotes the τth quantile function of BMI conditional on lagged BMI and all covariates. I estimate Equation

4.5 for the 25th, 50th, and 75th quantiles of the entire BMI distribution for each country[61]. The corresponding results are reported in Table 4.9.

4.5. Empirical results

4.5.1. The persistence of body weight

Table 4.4 and Table 4.5 report the marginal effects of lagged dependent variables, the initial obesity/overweight status and the financial situation measure *finstress* on the probability of being obese and overweight.

The results suggest strong state dependence of being obese and overweight. The marginal effects of lagged body weight and initial observation of weight status are both positive for all countries and such effects are strongly significant in general. The marginal effect of being obese in the previous wave on the probability of being obese now is higher in Italy (0.198) and Spain (0.160) and lower in Switzerland (0.027) compared to other countries. In a nutshell, being obese in the previous wave is associated with a 6.8 percent to 19.8 percent higher likelihood of being obese. Being overweight or obese in the previous wave is associated with an 11.5 to 19.7 percent higher chance of being overweight or obese. Such association is significant at the 1 percent significance level.

It is interesting to note that the marginal effect of the initial observation of being obese/overweight is almost twice as large as that of lagged obese/overweight status. To be specific, being obese in the first wave is associated with an 18.6 to 31.0 percent higher chance of being obese now, whilst being overweight in the first wave is associated with 24.0 to 35.6

[61] I also estimated Equation 4.5 at the 10th, 30th, 50th, 70th and 90th quantiles of BMI for each country. The results (not reported for brevity, but available upon request) only show marginal differences compared to those at the 25th, 50th, and 75th quantiles. Specifically, the magnitude trends of lagged BMI and financial stress remain unchanged.

percent higher chance of being overweight now. The large marginal effect of the initial observation of one's weight states can be partially explained as follows. Firstly, the initial observation here is not the true initial weight of each individual. Secondly, although I control for the individual heterogeneities at my best by modelling the initial weight as a function of the initial observations of all time-varying confounds, it is likely that there are other omitted factors that affect one's initial weight such as parents' weight, childhood socioeconomic status and diet. The effects of the true initial weight and the omitted variables are thus included in the effect of $Obesity_1$ / $Overweight_1$ in the estimations, which is, consequently, higher.

To sum up, the estimated marginal effects suggest that there is a positive and significant link between previous and current body weight. This confirms that individuals who are obese/overweight are much more likely to be obese/overweight subsequently. In addition, the large marginal effect of initial body weight may also reflect a positive link between the initial weight and unobserved individual heterogeneities that contribute to a higher body weight.

4.5.2. The role of financial distress

In Table 4.4, I find a significantly positive association between financial stress and the probability of being obese in Austria, Sweden, but a negative one in Belgium. *Not being able to make monthly ends meet* is associated with a 4.1 percent and a 2.9 percent higher chance of being obese in Austria and Sweden respectively, and a 1.9 percent lower chance of being obese in Belgium. In Table 4.5, the association between financial stress and being overweight is found for Spain only. Having financial stress is linked to a 3.6 percent higher chance of being overweight in the Spanish sample. Although in the summary statistics, I observe significantly higher prevalence of obesity in the financial stressed sample for all countries, the results show that financial situation is only weakly linked to being obese/overweight in general and even works in the opposite way for one country (Belgium). It is only significant for specific countries and the magnitude of such effect is rather small after controlling for the dynamics of obesity and individual heterogeneity.

My findings are consistent with Keese and Schmitz (2014) where no significant association between debt and obesity is found after controlling for individual time-invariant heterogeneity in Germany. My results contrast with those in Guariglia et al. (2018) who find a strongly negative correlation between a better financial situation (proxied by not having any debt) in the UK and the probability of being obese/overweight. The difference in my findings may be attributed to the different measures of financial situation used. In line with this argument, Borghans and Golsteyn (2006) have shown their finding on the relationship between time preference and body weight to be highly sensitive to the time preference proxies used. In Guariglia et al. (2018), not having debt, as a measure of financial health, reflects only one aspect of the objective financial situation within a household, it may not provide enough information on households' ability of monthly ends meet and capability of repaying debts. In other words, not having debt does not necessarily indicate not having financial stress. In addition, regional differences may also play a role, since the prevalence of household financial debt in the UK is higher than that of countries in my sample, with the exception of Sweden and Denmark. However, I do find a positive link between having financial stress and being obese in Sweden, but not in Denmark. Besides, neither do I find a statistically significant link between being financially stressed and being overweight in Sweden nor in Denmark, indicating that the first explanation for the difference in significance between this study and Guariglia et al. (2018) may be more valid.

My findings are also different from those in similar studies conducted in the US (Adams and Moore, 2007, Averett and Smith, 2014), Australia (Siahpush et al., 2014, Rohde et al., 2017), Germany (Münster et al., 2009) and Switzerland (Guerra et al., 2015) in which a strongly significant correlation between financial stress and body weight have been found. A possible explanation to this difference is twofold.

First, the majority of the above-mentioned studies have adopted a cross-sectional econometrics framework. It is thus impossible for them to address the individual heterogeneity issue since each sample is observed only once. Second, for the studies using longitudinal data, body weight and body weight status are not treated as dynamic matters. If there exists a strong dependence between current and historical weight, ignoring historical weight information may lead to biased estimates.

4.5.3. Does financial distress affect all individuals equally?

Considering men and women have many genetic and behavioural differences and are likely to respond to financial stress differently, I further test if the effect of financial stress on obesity/overweight differs for males and females. To this end, I replace the financial stress dummy in Equation 4.4 by two interaction terms between weight variables and the gender dummy[62]. The marginal effects of the two interactions are reported in Table 4.6 where Panel A presents the results for obesity and Panel B presents those of overweight.

For Austria and Sweden, where I have found a significant positive association between financial stress and the probability of being obese, I further find that this association only exists for women in Austria and for men in Sweden. Having financial stress is associated with a 6.1 percent higher chance of being obese for Austrian women and a 5.2 percent higher chance for Swedish men. In addition, I also find such a link for Spanish and Swiss women, and Italian men.

---

[62] The two interactions are *finstress***female*, and *finstress**(1-*female*)

Having financial stress is associated with a 3.4, 3.5 and 8.7 percent higher chance of being obese in the Spanish women, Italian men, and Swiss women sample respectively.

In Panel B, in addition to Spain, the positive link between financial stress and being overweight is also found for Germany. Having financial stress contributes to a 5.0 percent higher probability of being overweight for German women and a 3.4, and 3.9 percent higher probability for both Spanish men and women, respectively.

4.5.4. Demographics, SES factors and beyond

Table 4.7 and Table 4.8 report the marginal effects of other covariates in Equation 4.4 on the probability of being obese and overweight respectively. There are several consistencies among countries.

The effects of age and gender are generally not significant. After controlling for the state dependence of body weight status, one additional year of education attainment is significantly associated with a 0.69 percent lower chance of being obese in Germany. The corresponding percentages for Spain, Italy, Denmark and Switzerland are 0.43, 0.61, 0.50 and 0.40. Having limited mobility is associated with a higher probability of being obese. Such association is statistically significant for Spain, Italy, France, Denmark and Belgium. One additional point in the EURO-D depression scale is associated with a 0.64, 0.73 and 0.57 percent lower probability of being obese for France, Denmark and Belgium. This finding indicates worsening mental health is associated with weight loss. A good self-perceived health status is associated with a 2.36, 2.33, 2.40 and 4.24 percent lower chance of being obese for Sweden, Italy, France, and Switzerland, respectively.

Marital status plays a mixed role. Marital status is found to be significantly correlated to the probability of being obese in Denmark. Compared to single individuals, those who are married, divorced or widowed are associated with an 18.2, 17.1, and 19.4 percent higher chance of being obese in Denmark. However, being widowed is negatively associated with the occurrence of obesity in Germany and Belgium.

The marginal effect of being retired is only significant for Germany and Sweden. Being retired is associated with a 3.7 percent higher probability of being obese in Germany but a 2.3 percent lower probability in Sweden. These mixed results may be due to different sedentariness levels of jobs prior to retirement. Intuitively, those who retire from strenuous jobs may experience a large drop in work-related exercise and gain weight as a consequence, while others do not experience similar drops. These results are consistent with Goldman et al. (2008) and Godard (2016) who do not find a significant and generalised relationship between retirement and weight gain.

Income is found to be negatively associated with the probability of being obese in Sweden. Household real assets are negatively associated with the probability of being obese in Belgium. Yet, both marginal effects are only statistically significant at the 10 percent level. This finding is consistent with Cawley et al. (2010) who find only very small impacts of income and wealth on body weight in natural experiments.

I do not find a significant association between having a history of smoking and the probability of being obese. The sign of the impact of smoking history on obesity is negative in general but the marginal effect is not significant in general. Being physical inactive is significantly associated with a 6.2 and 2.3 percent higher chance of being obese in Austria and Italy respectively, but the same does not hold for other countries. Those who have reported a poor self-perceived health status are associated with a 6.4 percent higher chance of being obese in Switzerland only.

Similar above-mentioned patterns are found for the probability of being overweight with the exception of poor self-perceived health status where good health is found to be associated with a lower chance of being overweight. This is because weight loss could be a consequence of poor health (Willett, 1997). Education level is negatively associated with the estimated probability of being overweight, but such effect is only significant in Spain and Switzerland. Marital status does not affect the estimated probability of being overweight in general. Income and assets are negatively associated with the probability of overweight, but the magnitude of such impact is small and not statistically significant. Having limited mobility is positively linked to being overweight and such link is significant in Austria, Sweden and Spain. The marginal effect of the EURO-D score is negative in general and significant for Austria, Germany, Spain and France. Poor self-perceived health status is negatively associated with the probability of being overweight and such effect is significant in Sweden, Italy and Belgium. These associations are consistent with the existing literature such as Siahpush et al. (2014) and Guariglia et al. (2018).

4.5.5. Quantile regressions

It is plausible that individuals with different weight status do not response to financial stress identically. To allow for the possibility that the effect of financial stress changes over the distribution of BMI, I estimate Equation 4.5 in a QR setting.

Table 4.9 reports the quantile regression results of selected variables. The full QR results are reported in Appendix 4.2. The results show that the magnitude of lagged BMI increases with the quantiles of BMI. The estimated coefficients of BMI_{t-1} are smallest at the 25th quantile, and largest at the 75th quantile for all countries. The highly significant and positive coefficients of lagged BMI confirm the general existence of the state dependence of body weight, and such dependence is stronger at the higher quantiles of BMI for all countries.

As for financial stress, although the magnitude of the coefficients associated with financial stress increase with BMI, they are not statistically significant in most cases with the exceptions of two countries. Specifically, for Spain, being financially stressed is positively associated with a 0.34 units higher BMI (that is about 1kg heavier in weight for a 170cm person) at the 75th quantile. For France, being financially stressed is associated with a BMI higher by 0.11 units and 0.20 units at the 50th and 75th quantiles respectively.

4.5.6. Summary of main findings

Overall, my results show strong state dependence of body weight measured by the occurrence of obesity, overweight, and BMI in all country subsamples. Such state dependence is robust to different model specifications and body weight indicators. The positive link between financial stress and body weight are found in few countries, namely Austria, Germany, Sweden, Spain, Italy and France. But such positive link is sensitive to the model specifications and/or gender.

Being financially stressed increases the estimated probability of being obese by 4.1 percent in the full sample and by 5.8 percent in the female subsample in Austria. Yet, the same link is not found for the probability of being overweight and for BMI. In the German female subsample, I find that having financial stress is associated with a 4.8 percent higher chance of being overweight. In the Swedish and Italian male subsamples and in the Swiss female subsample, having financial stress is respectively associated with a 5.2, 3.5, and 6.3 percent higher probability of being obese, but the same does not hold for the probability of being overweight and for BMI.

Only in Spain, I consistently find a positive link between being financially stressed and body weight regardless of different model specifications. To be specific, having financial stress is associated with a 3.4 percent higher chance of being obese in the female subsample, a 3.2 and 4.2 percent higher chance of being overweight in the male and female subsamples, and 1 kg higher weight at the 70th quantiles of BMI[63].

[63] This estimation is made for a 170cm person.

4.6. Robustness tests

4.6.1. Corrected self-reported weight

In this study, BMI is calculated using respondents' self-reported weight information because the SHARE lacks actual weight information which is normally collected by a nurse or trained interviewer when the survey is taken place. The use of self-reported weight information raises several concerns. First, the weight variables might be underestimated if overweight/obese respondents underreport their weight in the surveys. Second, the estimators obtained in Section 4.5 would be biased if this reporting error is correlated with other characteristics included in my regression models such as education, gender and age. Third, the direction of this bias is hard to estimate because of the non-linear property of the probit specification I use.

To address these concerns, I follow Cawley et al. (2017) to correct the potential reporting errors exiting in the SHARE by using a validation dataset, namely the HRS, which contains both self-reported and measured weight information. The HRS is designed to study ageing issues in the US. The SHARE has closely followed the HRS regarding questionnaire design, sample selection and interviewer training (Börsch-Supan et al., 2005). Given the high level of comparability, the HRS is justified as the validation dataset for my study[64].

Starting from 2006, in each subsequent wave, half of the respondents in the HRS are randomly pre-selected for a face-to-face interview in which their weight is measured by a trained interviewer. The main interview is conducted prior to this weight measure and the respondents are not aware that their weight would be measured later when they report weight.

[64] Although the English Longitudinal Study of Ageing (ELSA) is also highly comparable to SHARE and could be considered as a better candidate than the HRS because the UK is more closely related to other European countries in terms of geographic and cultural factors, it does not have both self-reported and measured weight information at the same time.

This approach ensures minimum timing difference between reported and measured weight. It also reflects actual reporting errors because the respondents do not know their actual weight would be measured later (Cawley et al., 2017).

I draw a sample from HRS wave 8 (2006) to wave 13 (2016) with non-missing measured/self-reported weight and age information[65]. I then estimate the following equation using the OLS method for men and women separately:

$$weight_{actual} = f\,(constant,\ weight_{reported},\ weight^2_{reported},\ weight^3_{reported},\ agedummy50,\ agedummy5155,\ agedummy5660,\ agedummy6165,\ agedummy6670,\ agedummy7175,\ agedummy7680,\ agedummy80) \quad (4.6)$$

The OLS coefficients (reported in Appendix 4.2) obtained in the HRS are then used to predict the measured weight based on self-reported weight, age and gender information in the SHARE. This step assumes the relationship between actual weight and self-reported weight are the same in both datasets. This is, of course, a strong assumption. However, considering that HRS is a sibling study of SHARE and comparability widely exists between them (Börsch-Supan et al., 2005), I expect this transportability truly exists.

The relationship between corrected weight and self-reported weight in the SHARE are presented in Table 4.10. Using corrected weight, the prevalence of obesity and overweight in my sample is reported in Table 4.11. I then reconstruct the binary weight variables *overweight* and *obese*, and repeat the analyses described in Section 4.4.1.

[65] Wave 8 is the first wave to include measured body weight and wave 13 is the most recent wave available in the HRS.

The average corrected weight is 1.71 kg and 6.57 kg higher than average self-reported weight for females and males respectively. After correcting the self-reported body weight, the prevalence of obesity/overweight and BMI both increase compared to that using original respondents' self-reported weight. Regression results using corrected weight information are reported in Tables 4.12 and 4.13.

The results confirm the general existence of body weight status persistence. Being obese/overweight in the previous wave is strongly correlated with a higher probability of being obese/overweight in the subsequent wave. However, the link between financial stress and body weight is weakened. To be specific, the positive association between experiencing financial stress and the probability of being obese or overweight is only found in the Austrian and German female subsample. I still find such an association for both *obesity* and *overweight* in the Spanish female subsample. After controlling for possible reporting errors, the difference in obesity/overweight between individuals with financial stress and those without drops and so does the significance level of financial stress in my models. Since the difference between self-reported weight and corrected weight is larger in the male subsample, the significance level of the interaction $finstress_t*male$ declines significantly.

4.6.2. An objective measure of financial stress – high financial debt (*highdebt*)

I further test if I still find difference in weight status between the financially stressed and non-stressed groups using an objective measure of financial stress. Bridges and Disney (2010) have questioned the precision of using the self-perceived financial situation as a proxy for the real financial situation. The self-reported financial situation is likely to be affected by individuals' characteristics. For example, those who are depressed or anxious may perceive financial difficulties in a different way from other individuals (Bridges and Disney, 2010). Furthermore, respondents who receive government subsides may have incentives to underreport their financial situation if they see self-reported financial difficulties as a justification for receiving aid. To address this issue, I construct an objective indicator of financial stress. To be specific, I classify those who own financial liabilities higher than the average financial liability within the same country in the same wave as financially stressed individuals[66]. Table 4.14 presents the percentage of individuals having high financial liabilities. Among all countries, Sweden and Denmark have the highest and second highest proportion of individuals with high financial debt. This is consistent with the fact that household debt is more prevalent in Nordic countries compared to that of other European counties (EU Statistics on Income and Living Conditions, 2016). Italy and Spain have a relatively low proportion of individuals with high financial liabilities compared to that of other sampled countries. I also find that Switzerland has the lowest proportion of respondents having high financial debt. This is due to the average financial liability being high in Switzerland, thus the benchmark of *highdebt* is higher than other countries. Therefore, the proportion of respondents having high debt is low in Switzerland.

Table 4.15 and 4.16 present the marginal effects of financial stress measured by having high financial debt on the probability of being obese and overweight. I find having high financial debt is associated with a 4.98 percent higher chance of being obese and a 9.38 percent higher chance of being overweight in the German female subsample. In the Spanish female subsample, having high financial debt is associated with a 7.85 percent higher probability of being overweight, but the same does not apply to obesity. I find an opposite effect of financial stress in the Italian female subsample – having high financial debt is associated with a 4.04 percent lower chance of being obese. It is worth mentioning that I do not find a statistically

[66] I have tried the median of financial liabilities as another benchmark for defining *highdebt*. The results do not change. The correlation between financial stress and body weight status does not generally exist in all countries.

significant relationship between having high financial debt and being obese/overweight in Nordic countries where household debt is more prevalent compared to other countries.

Selenko and Batinic (2011) and Drentea and Lavrakas (2000) find a clear distinction between measuring debt objectively and subjectively. Subjective perceptions of bearing debts are significantly associated with mental and physical health outcomes, while the actual amount of debt is not as significant. In the present study, when the subjective financial stress measure is used, the positive link between financial stress and body weight is more evident. When the objective financial stress measure is used, the link disappears in most of the sampled countries. This suggests that financial stress itself may have limited impact on body weight. It is one's perception of his/her financial situation which matters. That is to say, objective financial stress does not necessary indicate the presence of subjective financial stress. Table 4.17 reports the correlation coefficient between *finstress* and *highdebt* where we can see that the correlation between the subjective financial stress (*finstress*) and the objective financial stress (*highdebt*) is only 0.03 and significant at the 5 percent level. Individuals who are less confident in their ability to cope with difficulties may be more likely to report subjective financial difficulties and more likely to respond to their financial difficulties.

4.7. Discussion

4.7.1. Does financial stress matter at all?

My findings show a weak link between financial stress and body weight. After controlling for the state dependence of body weight, the significance level of the financial situation decreases dramatically[67], indicating the incidence of obesity/overweight in my sample is largely driven by the history of being obese or overweight. Financial stress matters for some countries (subgroups), but the extent of such effect is limited. My findings also suggest that having subjective financial stress is more likely to be associated with a higher chance of being overweight/obese than having objective financial stress. By contrast, high levels of financial debt are generally not found to be associated with a higher probability of being overweight/obese.

A possible explanation for the insignificance of financial difficulty in several of my models is twofold. First, the effect of financial stress may be captured by other factors, for example, the EURO-D, which is a measure of mental health. There is a well-established literature which has found that financial difficulty is associated with worsened mental health (Bridges and Disney, 2010, Selenko and Batinic, 2011). Second, the effect of financial stress on body weight may be both positive and negative, i.e. financial stress may cause both weight losses or weight gains, which may lead to an overall ambiguous effect. More specifically, when experiencing financial stress, individuals are prone to binge eating or eating more calorie-dense

[67] The marginal effect of financial stress is strongly significant at the 1 percent level for all countries if the lagged dependent variable and initial observations of body weight are not controlled for. These results are not reported for brevity, but available upon request.

food leading to increase of body weight. However, stress may also lead to lower appetite which contributes to weight losses.

In addition, I also notice that the positive association between financial stress and body weight is less prevalent when I measure financial stress objectively. Subjective financial stress measured by *finstress* is associated with a higher chance of being obese/overweight in Austria, Germany, Sweden, Italy, and Switzerland. By contrast, my objective measure of financial stress is found to be associated with a higher probability of being obese/overweight in Germany and Spain. In addition, in Italy, a negative association is found between a high amount of debt and the probability of being obese is detected in the female subsample. These difference are in line with Selenko and Batinic (2011) and Drentea and Lavrakas (2000), who find that subjective perceptions of bearing debts are significantly associated with health outcomes, while the actual amount of debt is not as significant.

4.7.2. Limitations

Although I apply a rigorous econometric framework which controls for the state dependence of body weight as well as individual heterogeneity, only associations between financial situation and body weight (rather than causal effects) can be identified. Moreover, the possible endogeneity of the financial stress indicator has not been addressed. In addition, the sample I construct may not be representative for the whole population in Europe due to the balanced panel structure. Besides, only nine EU countries are analysed in this comparative study while other EU countries are left out because of data limitations. Finally, I have not yet investigated the possible mediators or moderators of the relationship between financial stress and body weight in countries where evidence for such a link is established. Furthermore, my approach of correcting self-reported weight is not flawless. This method is highly based on the assumption that the extent and direction of misreports in the SHARE are identical to those of the HRS. This assumption is very strong.

4.8. Conclusion

Obesity has been identified as a global epidemic in the last decade. According to the recent WHO estimation, obesity affects at least 20-30 percent and overweight affects at least 30-70 percent of adults in European regions. Excess body weight is linked to a higher risk of developing cardiovascular diseases, certain cancers and type II diabetes. It also causes physical disabilities and psychological problems. Moreover, the public cost of obesity is extremely high. In 2012, €81 billion public medical expenditure in the EU was directly or indirectly spent on treating obesity or obesity-related health (Hunt and Ferguson, 2014). In the context of household credit expansion and increasing financial fragility of European households following the Global Financial Crisis, I study the extent to which financial stress and weight gain are related among European adults aged 50 and over.

Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), I analyse 6,446 individuals from nine EU countries who have participated in all waves of SHARE from 2004 to 2014. The longitudinal setting of SHARE allows me to investigate the dynamics of body weight controlling for individual heterogeneity. The high level of cross-country comparability of SHARE enables me to conduct a comparative analysis across sampled European countries. I find some evidence for a positive link between financial stress and body weight in Austria, Germany, Sweden, Spain, Italy, France and Switzerland. This link is robust to correcting self-reported weight measures in Austria, Germany and Spain, and to using an alternative financial stress measure in Germany and Spain.

This study is the first to provide a comparative study on the topic of finance-obesity nexus among EU countries. It is also one of the first studies on obesity to consider the state dependence of obesity and to control for the initial conditions. In the context of increasing prevalence of obesity and overweight, this study sheds some light on understanding the epidemic of obesity in European countries. My findings suggest that policies targeted at improving citizens' financial stress coping strategy and reducing self-perceived financial stress may play a role in tackling the obesity epidemic in EU countries especially in Germany and Spain.

Table 4. 1 Structure of the balanced panel

Country	3-digit country code	No. of obs.
Austria	AUT	1,915
Germany	DEU	2,815
Sweden	SWE	4,150
Spain	ESP	3,595
Italy	ITA	4,680
France	FRA	3,520
Denmark	DNK	3,125
Switzerland	CHE	1,720
Belgium	BEL	6,710
Total		32,230

Source: SHARE, wave1/2/4/5/6

Table 4. 2 Summary statistics for data pooled across countries

Variable	Obs.		Mean	SD
BMI	32,230	Body Mass Index (Kg/m^2)	26.68	4.29
obesity	32,230	1 if BMI≥30, 0 otherwise	0.20	0.40
overweight	32,230	1 if BMI≥25, 0 otherwise	0.62	0.49
finstress	32,230	1 if financial stressed, 0 otherwise	0.29	0.45
retired	32,230	1 if retired, 0 otherwise	0.60	0.49
female	32,230	1 if female, 0 otherwise	0.57	0.49
yedu	32,230	Years of education attained	10.67	4.60
married	32,230	1 if married, 0 otherwise	0.73	0.44
divorced	32,230	1 if divorced, 0 otherwise	0.07	0.25
widowed	32,230	1 if widowed, 0 otherwise	0.15	0.35
age	32,230	Age at interview	67.70	9.26
hhsize	32,230	Number of household members	2.08	0.90
homeowner	32,230	1 if a homeowner, 0 otherwise	0.77	0.42
esmoked	32,230	1 if ever smoked, 0 otherwise	0.56	0.50
phinact	32,230	1 if being physical inactive, 0 otherwise	0.09	0.29
gali	32,230	1 if activity limited, 0 otherwise	0.42	0.49
goodhealth	32,230	1 if in good/very good/excellent self-perceived health status, 0 otherwise	0.69	0.46
poorhealth	32,230	1 if in poor self-perceived health status, 0 otherwise	0.07	0.25
eurod	32,230	Euro-D depression score (0-12)	2.27	2.16
foodpc	32,230	Food consumption per capita	0.33	0.19
hrass	32,230	Household real assets	24.74	30.66
thinc	32,230	Household total annual income	3.84	4.17

Notes: The unit of monetary variables namely *foodpc*, *hrass* and *thinc* is per 10,000 Euro (2010 price level); *foodpc*, *hrass*, *thinc* and *BMI* are winsorised at the bottom 1% and top 1%.

Table 4. 3 Sample means of weight variables by country and by financial situation

		No of obs.	*BMI*	*Overweight*	*Obese*
AUT	Financially stressed	373	27.802*	0.654	0.310**
	(% of full sample)	(19.48 %)			
	Not stressed	1,542	27.353	0.662	0.252
	Full sample	1,915	27.441	0.660	0.263
DEU	Financially stressed	582	28.081***	0.745***	0.278***
	(% of full sample)	(20.67 %)			
	Not stressed	2,233	26.449	0.599	0.165
	Full sample	2,815	26.774	0.629	0.188
SWE	Financially stressed	527	27.047***	0.629***	0.256***
	(% of full sample)	(12.69 %)			
	Not stressed	3,623	26.042	0.558	0.157
	Full sample	4,150	26.169	0.567	0.169
ESP	Financially stressed	1,839	28.425***	0.778***	0.322***
	(% of full sample)	(51.15 %)			
	Not stressed	1,756	27.357	0.685	0.222
	Full sample	3,595	27.804	0.732	0.273
ITA	Financially stressed	2,739	27.289***	0.667***	0.249***
	(% of full sample)	(58.52 %)			
	Not stressed	1,941	26.302	0.604	0.159
	Full sample	4,680	26.880	0.641	0.211
FRA	Financially stressed	959	27.280***	0.642***	0.264***
	(% of full sample)	(27.24 %)			
	Not stressed	2,561	26.238	0.554	0.183
	Full sample	3,520	26.522	0.578	0.205
DNK	Financially stressed	359	26.873***	0.646***	0.233***
	(% of full sample)	(11.48 %)			
	Not stressed	2,776	25.831	0.540	0.148
	Full sample	3,125	25.951	0.552	0.158
CHE	Financially stressed	203	26.154***	0.522	0.192***
	(% of full sample)	(11.80 %)			
	Not stressed	1,517	25.312	0.509	0.111
	Full sample	1,720	25.411	0.511	0.120
BEL	Financially stressed	1,632	27.350***	0.676***	0.257***
	(% of full sample)	(24.32 %)			
	Not stressed	5,078	26.502	0.608	0.189
	Full sample	6,710	26.708	0.625	0.205

Notes: *, **, *** denotes the mean difference between financial stressed and non-stressed group is significant at 1%, 5%, and 10% level respectively using standard t-tests.

Table 4. 4 Marginal effects of selected variables on the probability of being obese

	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
Obesity$_{t-1}$	0.0973***	0.0680***	0.0721***	0.160***	0.198***	0.0855***	0.0699***	0.0273	0.0996***
	(0.0277)	(0.0210)	(0.0170)	(0.0266)	(0.0245)	(0.0205)	(0.0193)	(0.0194)	(0.0151)
Obesity$_1$	0.310***	0.276***	0.252***	0.265***	0.186***	0.288***	0.247***	0.261***	0.266***
	(0.0278)	(0.0233)	(0.0192)	(0.0235)	(0.0239)	(0.0223)	(0.0213)	(0.0349)	(0.0153)
finstress$_t$	0.0411*	-0.00248	0.0290**	0.0190	0.0134	0.0111	-0.00807	0.0288	-0.0195**
	(0.0211)	(0.0139)	(0.0136)	(0.0148)	(0.0121)	(0.0134)	(0.0173)	(0.0191)	(0.00992)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Other controls include *age, female, yedu, married, widowed, divorced, retired, hhsize, thinc, hrass, gali, smoked, phinact, foodpc, eurod, goodhealth, poorhealth*. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 5 Marginal effects of selected variables on the probability of being overweight

	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
$Overweight_{t-1}$	0.136***	0.127***	0.134***	0.154***	0.128***	0.126***	0.153***	0.115***	0.197***
	(0.0351)	(0.0277)	(0.0229)	(0.0261)	(0.0225)	(0.0242)	(0.0286)	(0.0339)	(0.0213)
$Overweight_1$	0.327***	0.339***	0.356***	0.240***	0.348***	0.335***	0.345***	0.353***	0.279***
	(0.0330)	(0.0250)	(0.0216)	(0.0228)	(0.0193)	(0.0237)	(0.0276)	(0.0335)	(0.0216)
$finstress_t$	-0.0160	0.0176	-0.0279	0.0363**	-0.00475	-0.00620	0.0239	0.0142	-0.00287
	(0.0237)	(0.0203)	(0.0208)	(0.0160)	(0.0139)	(0.0155)	(0.0248)	(0.0293)	(0.0121)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Other controls include *age, female, yedu, married, widowed, divorced, retired, hhsize, thinc, hrass, gali, smoked, phinact, foodpc, eurod, goodhealth, poorhealth*. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 6 Differentiating the effect of financial stress on the probability of being obese/overweight for males and females

	Variables	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
Panel A										
Obesity	*finstress$_t$*female*	0.0613**	-0.00110	0.0133	0.0341*	-0.00344	0.0175	-0.0191	0.0875**	-0.0183
		(0.0280)	(0.0170)	(0.0183)	(0.0186)	(0.0152)	(0.0169)	(0.0208)	(0.0445)	(0.0113)
	*finstress$_t$*male*	0.00179	-0.00454	0.0526**	-0.00473	0.0355**	0.000334	0.00563	-0.0141	-0.0199
		(0.0380)	(0.0217)	(0.0286)	(0.0228)	(0.0171)	(0.0214)	(0.0263)	(0.0249)	(0.0152)
Panel B										
Overweight	*finstress$_t$*female*	-0.0235	0.0504*	-0.0426	0.0347*	-0.00384	-0.00434	0.0158	0.0357	-0.0211
		(0.0286)	(0.0271)	(0.0260)	(0.0205)	(0.0180)	(0.0186)	(0.0317)	(0.0360)	(0.0154)
	*finstress$_t$*male*	0.00202	-0.0220	-0.00180	0.0394*	-0.00600	-0.0106	0.0376	-0.0326	0.0274
		(0.0434)	(0.0290)	(0.0341)	(0.0236)	(0.0198)	(0.0266)	(0.0397)	(0.0527)	(0.0192)
	Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Other controls include *age, female, yedu, married, widowed, divorced, retired, hhsize, thinc, hrass, gali, smoked, phinact, foodpc, eurod, goodhealth, poorhealth*. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 7 Marginal effects of selected variables on the probability of being obese

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	AUT	DEU	SWE	ESP	ITA	FRA	DNK	CHE	BEL
age	0.0144	0.0284	0.0262	-0.0133	-0.0253	0.00266	-0.00809	0.0269	-0.00360
	(0.0321)	(0.0189)	(0.0162)	(0.0330)	(0.0443)	(0.0134)	(0.0222)	(0.0202)	(0.0107)
female	-0.00786	-0.0197	-0.00786	-0.00125	-0.00401	-0.00516	-0.0208	0.00485	-0.00897
	(0.0257)	(0.0174)	(0.0123)	(0.0235)	(0.0140)	(0.0163)	(0.0156)	(0.0169)	(0.0120)
yedu	-0.00182	-0.00690**	-0.00228	-0.00436**	-0.00606***	-0.00255	-0.00500**	-0.00404**	-0.00195
	(0.00252)	(0.00294)	(0.00161)	(0.00199)	(0.00191)	(0.00206)	(0.00255)	(0.00166)	(0.00159)
married	0.0143	-0.132	-0.130	-0.0279	0.0243	-0.0376	0.182**	-0.0420	-0.231
	(0.197)	(0.107)	(0.138)	(0.0540)	(0.0412)	(0.0737)	(0.0812)	(0.0534)	(0.144)
widowed	-0.0646	-0.188*	-0.141	-0.0571	-0.0163	-0.00740	0.171**	0.00546	-0.259*
	(0.200)	(0.113)	(0.138)	(0.0478)	(0.0320)	(0.0731)	(0.0851)	(0.0418)	(0.146)
divorced	0.195	-0.149	-0.126	-0.0729	0.177*	-0.0285	0.194**	-0.102	-0.189
	(0.231)	(0.104)	(0.143)	(0.135)	(0.0972)	(0.0748)	(0.0863)	(0.0752)	(0.141)
retired	-0.0140	0.0374**	-0.0227*	-0.0243	0.0175	-0.0182	0.0173	0.0157	0.00803
	(0.0213)	(0.0167)	(0.0130)	(0.0190)	(0.0149)	(0.0151)	(0.0155)	(0.0141)	(0.00998)
hhsize	-0.00753	-0.000235	-0.000385	0.00311	-0.00736	-0.0229*	-0.00721	-0.0141	-0.00847
	(0.0128)	(0.0134)	(0.0120)	(0.0102)	(0.00729)	(0.0119)	(0.0150)	(0.0116)	(0.00846)
thinc	-0.00760	-0.00198	-0.00334*	-0.00514	-0.00122	0.00267	-0.00291	0.000319	0.000782
	(0.00516)	(0.00299)	(0.00195)	(0.00628)	(0.00349)	(0.00281)	(0.00321)	(0.000692)	(0.000644)
hrass	-0.000255	-0.000622	-0.000129	0.000205	-0.000248	0.000145	-0.000236	0.000122	-0.000575**
	(0.000491)	(0.000396)	(0.000160)	(0.000312)	(0.000301)	(0.000232)	(0.000248)	(8.38e-05)	(0.000254)
gali	0.0227	0.00153	0.0117	0.0273*	0.0227*	0.0286**	0.0240*	-0.0211	0.0299***
	(0.0178)	(0.0138)	(0.00967)	(0.0164)	(0.0122)	(0.0122)	(0.0130)	(0.0143)	(0.00891)
esmoked	-0.0374	-0.00481	-0.0243	-0.00688	-0.0228	-0.0213	-0.0274	-0.0169	0.00892
	(0.0291)	(0.0220)	(0.0164)	(0.0294)	(0.0221)	(0.0200)	(0.0212)	(0.0215)	(0.0147)
phinact	0.0615**	0.0145	0.0149	0.0135	0.0230*	0.00695	0.0356	0.0136	-0.0202
	(0.0275)	(0.0238)	(0.0202)	(0.0191)	(0.0136)	(0.0183)	(0.0242)	(0.0227)	(0.0128)
foodpc	0.105	0.0581	0.0128	0.0979	0.0519	-0.0202	-0.0139	-0.0493**	0.0211
	(0.0696)	(0.0514)	(0.0421)	(0.0618)	(0.0452)	(0.0272)	(0.0460)	(0.0248)	(0.0229)
eurod	-0.00560	0.00341	-0.00173	-0.000709	-0.00107	-0.00640**	-0.00729**	-0.00433	-0.00570***
	(0.00454)	(0.00344)	(0.00285)	(0.00310)	(0.00241)	(0.00293)	(0.00367)	(0.00361)	(0.00219)
goodhealth	0.00768	0.000428	-0.0236**	-0.0118	-0.0233*	-0.0240*	-0.00992	-0.0424**	-0.00966

	(0.0200)	(0.0145)	(0.0112)	(0.0168)	(0.0126)	(0.0138)	(0.0152)	(0.0167)	(0.0101)
poorhealth	-0.0295	-0.0156	-0.0280	-0.0184	-0.0145	0.0227	0.0172	0.0640**	-0.00625
	(0.0322)	(0.0212)	(0.0197)	(0.0217)	(0.0170)	(0.0185)	(0.0269)	(0.0320)	(0.0186)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Other control variables include $obesity_{t-1}$, $obesity_1$, *finstress*. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 8 Marginal effects of selected variables on the probability of being overweight

	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
age	0.00518	0.0488**	0.000799	-0.0168	0.0266	0.00922	0.0232	-0.000350	-0.0105
	(0.0355)	(0.0242)	(0.0209)	(0.0359)	(0.0470)	(0.0150)	(0.0288)	(0.0309)	(0.0147)
female	-0.0247	-0.0657***	-0.00999	-0.0568**	-0.0377**	-0.0390**	-0.0289	-0.0510**	-0.0224
	(0.0274)	(0.0231)	(0.0165)	(0.0256)	(0.0186)	(0.0187)	(0.0178)	(0.0256)	(0.0138)
yedu	-0.00248	-0.00479	-0.00170	-0.00641***	-0.00327	-9.87e-06	0.00384	-0.00813***	-0.00116
	(0.00259)	(0.00317)	(0.00208)	(0.00210)	(0.00228)	(0.00231)	(0.00296)	(0.00261)	(0.00173)
married	-0.00913	0.172	0.0649	-0.0249	-0.0160	0.0770	0.0570	0.0546	0.0399
	(0.144)	(0.165)	(0.108)	(0.0578)	(0.0523)	(0.0960)	(0.144)	(0.0717)	(0.222)
widowed	-0.0803	0.170	0.103	0.0352	-0.00985	0.0973	0.0934	-0.0458	-0.0464
	(0.150)	(0.169)	(0.112)	(0.0505)	(0.0421)	(0.0956)	(0.146)	(0.0583)	(0.223)
divorced	-0.0339	0.144	0.0871	0.0716	-0.0592	0.0429	0.00446	0.174	-0.00247
	(0.230)	(0.186)	(0.124)	(0.120)	(0.125)	(0.114)	(0.140)	(0.127)	(0.219)
retired	-0.0101	0.00657	-0.00964	0.0189	0.0271	0.0342**	-0.0171	-0.00968	0.0202
	(0.0249)	(0.0207)	(0.0175)	(0.0202)	(0.0173)	(0.0171)	(0.0205)	(0.0212)	(0.0126)
hhsize	-0.0157	0.0216	0.00902	0.0180	-0.0140	0.0109	0.0252	-0.0250	-0.0118
	(0.0142)	(0.0167)	(0.0151)	(0.0111)	(0.00914)	(0.0132)	(0.0173)	(0.0160)	(0.00977)
thinc	0.00319	0.00499	-0.00104	0.00213	-0.00134	-0.00541*	-0.00270	-0.000673	0.000962
	(0.00568)	(0.00335)	(0.00257)	(0.00637)	(0.00376)	(0.00315)	(0.00405)	(0.00105)	(0.000804)
hrass	-0.000581	-0.000940**	0.000386*	0.000430	1.68e-05	-0.000351	0.000253	1.68e-05	-4.98e-05
	(0.000515)	(0.000409)	(0.000222)	(0.000339)	(0.000328)	(0.000248)	(0.000272)	(0.000127)	(0.000273)
gali	0.0366*	-0.0244	0.0308**	0.0380**	0.00812	6.55e-05	-0.00389	0.0194	0.0125
	(0.0209)	(0.0175)	(0.0134)	(0.0183)	(0.0140)	(0.0145)	(0.0171)	(0.0209)	(0.0108)
esmoked	-0.00171	-0.0446	-0.0218	0.0174	-0.00555	-0.0102	-0.0314	-0.0216	0.0158
	(0.0349)	(0.0279)	(0.0222)	(0.0316)	(0.0233)	(0.0224)	(0.0276)	(0.0322)	(0.0179)
phinact	0.00292	-0.0250	0.0109	0.00635	0.0167	-0.00290	-0.0320	0.00335	0.0179
	(0.0309)	(0.0323)	(0.0322)	(0.0213)	(0.0157)	(0.0234)	(0.0344)	(0.0442)	(0.0173)
foodpc	-0.120	-0.0259	-0.00162	0.0245	0.0439	-0.00743	-0.0545	0.00587	0.0225
	(0.0745)	(0.0641)	(0.0567)	(0.0662)	(0.0510)	(0.0311)	(0.0581)	(0.0353)	(0.0276)
eurod	-0.0149***	-0.0131***	-0.000689	-0.00773**	0.00209	-0.00910***	-0.00729	-0.00794	-0.00284
	(0.00512)	(0.00454)	(0.00385)	(0.00335)	(0.00282)	(0.00325)	(0.00472)	(0.00574)	(0.00271)
goodhealth	0.0575**	0.00190	-0.0202	-0.00426	-0.0119	0.0135	0.00301	0.0188	0.00446

	(0.0237)	(0.0194)	(0.0165)	(0.0186)	(0.0147)	(0.0159)	(0.0215)	(0.0288)	(0.0130)
poorhealth	0.00326	-0.0480	-0.0663**	-0.0342	-0.0423**	0.00217	0.0218	0.103	-0.0694***
	(0.0367)	(0.0302)	(0.0305)	(0.0244)	(0.0208)	(0.0253)	(0.0362)	(0.0775)	(0.0256)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Other control variables include $overweight_{t-1}$, $overweight_1$, *finstress*. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 9 Quantile regressions with clustered standard errors

		(1) 0.25	(2) 0.5	(3) 0.75
AUT	BMI_{t-1}	0.882***	0.949***	0.960***
		(0.0172)	(0.00861)	(0.0142)
	$finstress_t$	0.0944	0.0198	0.327
		(0.142)	(0.108)	(0.204)
DEU	BMI_{t-1}	0.905***	0.975***	0.986***
		(0.0126)	(0.00849)	(0.0114)
	$finstress_t$	0.0973	0.0257	0.133
		(0.120)	(0.0682)	(0.128)
SWE	BMI_{t-1}	0.918***	0.981***	1.001***
		(0.00934)	(0.00441)	(0.00748)
	$finstress_t$	-0.0152	0.00252	0.123
		(0.127)	(0.0681)	(0.128)
ESP	BMI_{t-1}	0.719***	0.845***	0.848***
		(0.0263)	(0.0140)	(0.0196)
	$finstress_t$	0.0454	0.152	0.344**
		(0.133)	(0.0955)	(0.167)
ITA	BMI_{t-1}	0.843***	0.917***	0.931***
		(0.0126)	(0.00965)	(0.0116)
	$finstress_t$	-0.0306	-0.0288	0.134
		(0.0881)	(0.0616)	(0.0882)
FRA	BMI_{t-1}	0.905***	0.961***	0.996***
		(0.00776)	(0.00551)	(0.0112)
	$finstress_t$	0.0717	0.110*	0.197**
		(0.0877)	(0.0574)	(0.0949)
DNK	BMI_{t-1}	0.924***	0.975***	0.996***
		(0.00880)	(0.00622)	(0.00949)
	$finstress_t$	0.225*	0.0750	0.0141
		(0.129)	(0.0898)	(0.128)
CHE	BMI_{t-1}	0.923***	0.965***	0.991***
		(0.0151)	(0.00948)	(0.0115)
	$finstress_t$	0.0231	-0.0103	0.185
		(0.142)	(0.122)	(0.177)
BEL	BMI_{t-1}	0.921***	0.969***	0.983***
		(0.00674)	(0.00451)	(0.00668)
	$finstress_t$	0.00177	-0.0169	0.0707
		(0.0634)	(0.0402)	(0.0626)

Notes: Other controls include *age*, *female*, *yedu*, *married*, *widowed*, *divorced*, *retired*, *hhsize*, *thinc*, *hrass*, *gali*, *smoked*, *phinact*, *foodpc*, *eurod*, *goodhealth*, *poorhealth*. *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Clustered standard errors are reported in parentheses. See Table 4.2 for complete definitions of all variables.

Table 4. 10 Mean difference of reported and corrected body weight in SHARE

	Female		Male	
Country	Weight	Corrected weight	Weight	Corrected weight
AUT	72.82	74.60	84.43	91.67
DEU	71.16	72.96	84.17	91.45
SWE	70.27	71.98	84.45	91.64
ESP	69.67	71.32	78.57	84.38
ITA	68.72	70.41	78.66	84.49
FRA	68.20	69.89	80.38	86.65
DNK	69.56	71.32	84.11	91.24
CHE	66.80	68.47	78.79	84.64
BEL	69.92	71.65	82.34	88.99
Average diff.		+1.71		+6.57

Table 4. 11 Prevalence of overweight and obesity using corrected weight information

	Female			Male		
Country	*BMI*	*Obesity*	*Overweight*	*BMI*	*Obesity*	*Overweight*
AUT	28.10	0.33	0.65	29.94	0.43	0.84
DEU	27.21	0.23	0.64	29.45	0.34	0.84
SWE	26.52	0.20	0.59	28.82	0.33	0.79
ESP	28.66	0.33	0.77	29.89	0.40	0.89
ITA	27.40	0.26	0.66	29.10	0.35	0.83
FRA	27.04	0.24	0.57	28.85	0.35	0.78
DNK	26.23	0.19	0.54	28.69	0.33	0.79
CHE	25.80	0.16	0.49	27.73	0.24	0.74
BEL	27.07	0.15	0.62	29.27	0.38	0.84
Average	27.166	0.24	0.62	29.12	0.36	0.82

Table 4. 12 Marginal effects of selected variables on the probability of being obese using corrected weight information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUT	DEU	SWE	ESP	ITA	FRA	DNK	CHE	BEL
Obesity$_{t-1}$	0.134***	0.0865***	0.0953***	0.180***	0.163***	0.162***	0.0975***	0.0861***	0.143***
	(0.0330)	(0.0249)	(0.0195)	(0.0276)	(0.0236)	(0.0267)	(0.0216)	(0.0305)	(0.0179)
*finstress$_t$*female*	0.0561*	0.0149	0. 0150	0.0382*	0.0147	0.0183	-0.000947	0.0305	-0.0155
	(0.0325)	(0.0218)	(0.0202)	(0.0200)	(0.0178)	(0.0181)	(0.0268)	(0.0337)	(0.0134)
*finstress$_t$*male*	0.0216	-0.00831	0.0233	-0.00199	0.0198	0.00951	0.00453	0.00943	0.00370
	(0.416)	(0.0273)	(0.0289)	(0.0258)	(0.0202)	(0.0239)	(0.0303)	(0.0344)	(0.0175)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 13 Marginal effects of selected variables on the probability of being overweight using corrected weight information

VARIABLES	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
Overweight$_{t-1}$	0.141***	0.101***	0.100***	0.123***	0.109***	0.114***	0.132***	0.114***	0.158***
	(0.0337)	(0.0246)	(0.0212)	(0.0244)	(0.0202)	(0.0233)	(0.0263)	(0.0349)	(0.0191)
finstress$_t$**female*	-0.0259	0.0747***	-0.0279	0.0338*	-0.00691	0.00118	0.0409	-0.0244	-0.0119
	(0.0275)	(0.0267)	(0.0238)	(0.0175)	(0.0174)	(0.0200)	(0.0295)	(0.0379)	(0.0148)
finstress$_t$**male*	-0.0447	-0.0000078	0.0399	-0.0188	-0.0148	-0.0174	0.000407	-0.0185	-0.00175
	(0.0430)	(0.0286)	(0.0317)	(0.0198)	(0.0178)	(0.0264)	(0.0389)	(0.0464)	(0.0188)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 14 Percentage of respondents having high financial debt by country

Country	Statistics	*highdebt=1*
AUT	Mean	0.090862
	Sd	0.287487
DEU	Mean	0.111545
	Sd	0.314862
SWE	Mean	0.180482
	Sd	0.384635
ESP	Mean	0.073714
	Sd	0.261340
ITA	Mean	0.081838
	Sd	0.274146
FRA	Mean	0.142046
	Sd	0.349146
DNK	Mean	0.163200
	Sd	0.369607
CHE	Mean	0.040116
	Sd	0.196289
BEL	Mean	0.094188
	Sd	0.292112
Total	Mean	0.111573
	Sd	0.314845

Notes: *highdebt* is a dummy variable which indicates having financial liability higher than the country/wave average, and 0 otherwise.

Table 4. 15 Marginal effects of selected variables on the probability of being obese

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUT	DEU	SWE	ESP	ITA	FRA	DNK	CHE	BEL
*highdebt$_t$*male*	-0.0106	0.0361	-0.0107	0.0404	0.0338	0.00578	0.0222	0.00923	0.00327
	(0.0439)	(0.0336)	(0.0166)	(0.0447)	(0.0290)	(0.0226)	(0.0249)	(0.0404)	(0.0206)
*highdebt$_t$*female*	-0.00981	0.0498*	-0.0123	0.0350	-0.0404*	-0.0252	-0.0139	-0.0199	0.00974
	(0.0350)	(0.0269)	(0.0146)	(0.0368)	(0.0244)	(0.0200)	(0.0202)	(0.0286)	(0.0172)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Lagged dependent variable, as well as initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 16 Marginal effects of selected variables on the probability of being overweight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUT	DEU	SWE	ESP	ITA	FRA	DNK	CHE	BEL
*highdebt$_t$*male*	-0.0755	0.0559	0.0199	0.0136	-0.00675	-0.0281	-0.0339	-0.0399	-0.0344
	(0.0561)	(0.0391)	(0.0248)	(0.0450)	(0.0333)	(0.0262)	(0.0312)	(0.0668)	(0.0253)
*highdebt$_t$*female*	0.0430	0.0938***	-0.00272	0.0785**	0.0312	-0.0200	0.0310	-0.0182	0.0144
	(0.0446)	(0.0327)	(0.0238)	(0.0377)	(0.0309)	(0.0239)	(0.0291)	(0.0589)	(0.0241)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. Lagged dependent variable, as well as initial values of all time-varying variables are included in all regressions. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Table 4. 17 Correlation matrix between *finstress* and *highdebt*

	finstress	*highdebt*
finstress		0.03*
highdebt	0.03*	

Notes: Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman's rank correlation. * indicates significance at the 5% level.

Appendix 4.1 Regression Tables

Appendix Table 4.1a. Marginal effects of all regressors on the probability of being obese

VARIABLES	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
lobesity	0.0973***	0.0680***	0.0721***	0.160***	0.198***	0.0855***	0.0699***	0.0273	0.0996***
	(0.0277)	(0.0210)	(0.0170)	(0.0266)	(0.0245)	(0.0205)	(0.0193)	(0.0194)	(0.0151)
intobesity	0.310***	0.276***	0.252***	0.265***	0.186***	0.288***	0.247***	0.261***	0.266***
	(0.0278)	(0.0233)	(0.0192)	(0.0235)	(0.0239)	(0.0223)	(0.0213)	(0.0349)	(0.0153)
finstress1	0.0411*	-0.00248	0.0290**	0.0190	0.0134	0.0111	-0.00807	0.0288	-0.0195**
	(0.0211)	(0.0139)	(0.0136)	(0.0148)	(0.0121)	(0.0134)	(0.0173)	(0.0191)	(0.00992)
intfinstress1	0.00912	0.0662***	-0.000188	0.0291	-0.00133	0.0248	0.0146	0.00929	0.0207*
	(0.0269)	(0.0200)	(0.0168)	(0.0181)	(0.0142)	(0.0174)	(0.0208)	(0.0230)	(0.0120)
age	0.0144	0.0284	0.0262	-0.0133	-0.0253	0.00266	-0.00809	0.0269	-0.00360
	(0.0321)	(0.0189)	(0.0162)	(0.0330)	(0.0443)	(0.0134)	(0.0222)	(0.0202)	(0.0107)
female	-0.00786	-0.0197	-0.00786	-0.00125	-0.00401	-0.00516	-0.0208	0.00485	-0.00897
	(0.0257)	(0.0174)	(0.0123)	(0.0235)	(0.0140)	(0.0163)	(0.0156)	(0.0169)	(0.0120)
yedu	-0.00182	-0.00690**	-0.00228	-0.00436**	-0.00606***	-0.00255	-0.00500**	-0.00404**	-0.00195
	(0.00252)	(0.00294)	(0.00161)	(0.00199)	(0.00191)	(0.00206)	(0.00255)	(0.00166)	(0.00159)
married	0.0143	-0.132	-0.130	-0.0279	0.0243	-0.0376	0.182**	-0.0420	-0.231
	(0.197)	(0.107)	(0.138)	(0.0540)	(0.0412)	(0.0737)	(0.0812)	(0.0534)	(0.144)
widowed	-0.0646	-0.188*	-0.141	-0.0571	-0.0163	-0.00740	0.171**	0.00546	-0.259*
	(0.200)	(0.113)	(0.138)	(0.0478)	(0.0320)	(0.0731)	(0.0851)	(0.0418)	(0.146)
divorced	0.195	-0.149	-0.126	-0.0729	0.177*	-0.0285	0.194**	-0.102	-0.189
	(0.231)	(0.104)	(0.143)	(0.135)	(0.0972)	(0.0748)	(0.0863)	(0.0752)	(0.141)
retired	-0.0140	0.0374**	-0.0227*	-0.0243	0.0175	-0.0182	0.0173	0.0157	0.00803
	(0.0213)	(0.0167)	(0.0130)	(0.0190)	(0.0149)	(0.0151)	(0.0155)	(0.0141)	(0.00998)
hhsize	-0.00753	-0.000235	-0.000385	0.00311	-0.00736	-0.0229*	-0.00721	-0.0141	-0.00847
	(0.0128)	(0.0134)	(0.0120)	(0.0102)	(0.00729)	(0.0119)	(0.0150)	(0.0116)	(0.00846)
thinc	-0.00760	-0.00198	-0.00334*	-0.00514	-0.00122	0.00267	-0.00291	0.000319	0.000782
	(0.00516)	(0.00299)	(0.00195)	(0.00628)	(0.00349)	(0.00281)	(0.00321)	(0.000692)	(0.000644)

hrass	-0.000255	-0.000622	-0.000129	0.000205	-0.000248	0.000145	-0.000236	0.000122	-0.000575**
	(0.000491)	(0.000396)	(0.000160)	(0.000312)	(0.000301)	(0.000232)	(0.000248)	(8.38e-05)	(0.000254)
gali	0.0227	0.00153	0.0117	0.0273*	0.0227*	0.0286**	0.0240*	-0.0211	0.0299***
	(0.0178)	(0.0138)	(0.00967)	(0.0164)	(0.0122)	(0.0122)	(0.0130)	(0.0143)	(0.00891)
esmoked	-0.0374	-0.00481	-0.0243	-0.00688	-0.0228	-0.0213	-0.0274	-0.0169	0.00892
	(0.0291)	(0.0220)	(0.0164)	(0.0294)	(0.0221)	(0.0200)	(0.0212)	(0.0215)	(0.0147)
phinact	0.0615**	0.0145	0.0149	0.0135	0.0230*	0.00695	0.0356	0.0136	-0.0202
	(0.0275)	(0.0238)	(0.0202)	(0.0191)	(0.0136)	(0.0183)	(0.0242)	(0.0227)	(0.0128)
foodpc	0.105	0.0581	0.0128	0.0979	0.0519	-0.0202	-0.0139	-0.0493**	0.0211
	(0.0696)	(0.0514)	(0.0421)	(0.0618)	(0.0452)	(0.0272)	(0.0460)	(0.0248)	(0.0229)
eurod	-0.00560	0.00341	-0.00173	-0.000709	-0.00107	-0.00640**	-0.00729**	-0.00433	-0.00570***
	(0.00454)	(0.00344)	(0.00285)	(0.00310)	(0.00241)	(0.00293)	(0.00367)	(0.00361)	(0.00219)
goodhealth	0.00768	0.000428	-0.0236**	-0.0118	-0.0233*	-0.0240*	-0.00992	-0.0424**	-0.00966
	(0.0200)	(0.0145)	(0.0112)	(0.0168)	(0.0126)	(0.0138)	(0.0152)	(0.0167)	(0.0101)
poorhealth	-0.0295	-0.0156	-0.0280	-0.0184	-0.0145	0.0227	0.0172	0.0640**	-0.00625
	(0.0322)	(0.0212)	(0.0197)	(0.0217)	(0.0170)	(0.0185)	(0.0269)	(0.0320)	(0.0186)
w3	-0.0513	-0.141*	-0.0946	0.0567	0.0729	0.0172	0.0234	-0.113	-0.00587
	(0.140)	(0.0855)	(0.0747)	(0.141)	(0.181)	(0.0680)	(0.0952)	(0.0937)	(0.0467)
w4	-0.0838	-0.171	-0.150	0.0717	0.109	0.0250	0.0255	-0.157	0.0135
	(0.201)	(0.121)	(0.107)	(0.205)	(0.268)	(0.0933)	(0.139)	(0.132)	(0.0675)
w5	-0.116	-0.242	-0.191	0.0991	0.163	0.0118	0.0399	-0.223	0.00822
	(0.265)	(0.159)	(0.139)	(0.271)	(0.357)	(0.120)	(0.184)	(0.173)	(0.0888)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE Probit model. Initial values of all time-varying variables are included in all regressions but omitted for brevity. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Appendix Table 4.1b Marginal effects of all regressors on the probability of being overweight

VARIABLES	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
loverweight	0.136***	0.127***	0.134***	0.154***	0.128***	0.126***	0.153***	0.115***	0.197***
	(0.0351)	(0.0277)	(0.0229)	(0.0261)	(0.0225)	(0.0242)	(0.0286)	(0.0339)	(0.0213)
intoverweight	0.327***	0.339***	0.356***	0.240***	0.348***	0.335***	0.345***	0.353***	0.279***
	(0.0330)	(0.0250)	(0.0216)	(0.0228)	(0.0193)	(0.0237)	(0.0276)	(0.0335)	(0.0216)
finstress1	-0.0160	0.0176	-0.0279	0.0363**	-0.00475	-0.00620	0.0239	0.0142	-0.00287
	(0.0237)	(0.0203)	(0.0208)	(0.0160)	(0.0139)	(0.0155)	(0.0248)	(0.0293)	(0.0121)
intfinstress1	0.0243	-0.0195	-0.0154	0.000273	-0.0515***	0.0315	-0.00527	0.0241	0.0191
	(0.0269)	(0.0274)	(0.0231)	(0.0195)	(0.0190)	(0.0198)	(0.0257)	(0.0332)	(0.0140)
age	0.00518	0.0488**	0.000799	-0.0168	0.0266	0.00922	0.0232	-0.000350	-0.0105
	(0.0355)	(0.0242)	(0.0209)	(0.0359)	(0.0470)	(0.0150)	(0.0288)	(0.0309)	(0.0147)
female	-0.0247	-0.0657***	-0.00999	-0.0568**	-0.0377**	-0.0390**	-0.0289	-0.0510**	-0.0224
	(0.0274)	(0.0231)	(0.0165)	(0.0256)	(0.0186)	(0.0187)	(0.0178)	(0.0256)	(0.0138)
yedu	-0.00248	-0.00479	-0.00170	-0.00641***	-0.00327	-9.87e-06	0.00384	-0.00813***	-0.00116
	(0.00259)	(0.00317)	(0.00208)	(0.00210)	(0.00228)	(0.00231)	(0.00296)	(0.00261)	(0.00173)
married	-0.00913	0.172	0.0649	-0.0249	-0.0160	0.0770	0.0570	0.0546	0.0399
	(0.144)	(0.165)	(0.108)	(0.0578)	(0.0523)	(0.0960)	(0.144)	(0.0717)	(0.222)
widowed	-0.0803	0.170	0.103	0.0352	-0.00985	0.0973	0.0934	-0.0458	-0.0464
	(0.150)	(0.169)	(0.112)	(0.0505)	(0.0421)	(0.0956)	(0.146)	(0.0583)	(0.223)
divorced	-0.0339	0.144	0.0871	0.0716	-0.0592	0.0429	0.00446	0.174	-0.00247
	(0.230)	(0.186)	(0.124)	(0.120)	(0.125)	(0.114)	(0.140)	(0.127)	(0.219)
retired	-0.0101	0.00657	-0.00964	0.0189	0.0271	0.0342**	-0.0171	-0.00968	0.0202
	(0.0249)	(0.0207)	(0.0175)	(0.0202)	(0.0173)	(0.0171)	(0.0205)	(0.0212)	(0.0126)
hhsize	-0.0157	0.0216	0.00902	0.0180	-0.0140	0.0109	0.0252	-0.0250	-0.0118
	(0.0142)	(0.0167)	(0.0151)	(0.0111)	(0.00914)	(0.0132)	(0.0173)	(0.0160)	(0.00977)
thinc	0.00319	0.00499	-0.00104	0.00213	-0.00134	-0.00541*	-0.00270	-0.000673	0.000962
	(0.00568)	(0.00335)	(0.00257)	(0.00637)	(0.00376)	(0.00315)	(0.00405)	(0.00105)	(0.000804)
hrass	-0.000581	-0.000940**	0.000386*	0.000430	1.68e-05	-0.000351	0.000253	1.68e-05	-4.98e-05
	(0.000515)	(0.000409)	(0.000222)	(0.000339)	(0.000328)	(0.000248)	(0.000272)	(0.000127)	(0.000273)
gali	0.0366*	-0.0244	0.0308**	0.0380**	0.00812	6.55e-05	-0.00389	0.0194	0.0125

	(0.0209)	(0.0175)	(0.0134)	(0.0183)	(0.0140)	(0.0145)	(0.0171)	(0.0209)	(0.0108)
esmoked	-0.00171	-0.0446	-0.0218	0.0174	-0.00555	-0.0102	-0.0314	-0.0216	0.0158
	(0.0349)	(0.0279)	(0.0222)	(0.0316)	(0.0233)	(0.0224)	(0.0276)	(0.0322)	(0.0179)
phinact	0.00292	-0.0250	0.0109	0.00635	0.0167	-0.00290	-0.0320	0.00335	0.0179
	(0.0309)	(0.0323)	(0.0322)	(0.0213)	(0.0157)	(0.0234)	(0.0344)	(0.0442)	(0.0173)
foodpc	-0.120	-0.0259	-0.00162	0.0245	0.0439	-0.00743	-0.0545	0.00587	0.0225
	(0.0745)	(0.0641)	(0.0567)	(0.0662)	(0.0510)	(0.0311)	(0.0581)	(0.0353)	(0.0276)
eurod	-0.0149***	-0.0131***	-0.000689	-0.00773**	0.00209	-0.00910***	-0.00729	-0.00794	-0.00284
	(0.00512)	(0.00454)	(0.00385)	(0.00335)	(0.00282)	(0.00325)	(0.00472)	(0.00574)	(0.00271)
goodhealth	0.0575**	0.00190	-0.0202	-0.00426	-0.0119	0.0135	0.00301	0.0188	0.00446
	(0.0237)	(0.0194)	(0.0165)	(0.0186)	(0.0147)	(0.0159)	(0.0215)	(0.0288)	(0.0130)
poorhealth	0.00326	-0.0480	-0.0663**	-0.0342	-0.0423**	0.00217	0.0218	0.103	-0.0694***
	(0.0367)	(0.0302)	(0.0305)	(0.0244)	(0.0208)	(0.0253)	(0.0362)	(0.0775)	(0.0256)
w3	-0.0263	-0.177	0.0209	0.0632	-0.135	-0.0514	-0.0819	0.0531	0.00708
	(0.156)	(0.110)	(0.0963)	(0.153)	(0.192)	(0.0759)	(0.124)	(0.144)	(0.0637)
w4	-0.0173	-0.286*	-0.0147	0.0885	-0.201	-0.0492	-0.140	0.0462	0.0366
	(0.224)	(0.156)	(0.137)	(0.223)	(0.285)	(0.104)	(0.181)	(0.204)	(0.0922)
w5	-0.0504	-0.407**	-0.00623	0.107	-0.274	-0.0721	-0.186	0.00523	0.0625
	(0.295)	(0.205)	(0.179)	(0.294)	(0.379)	(0.134)	(0.239)	(0.266)	(0.122)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE Probit model. Initial values of all time-varying variables are included in all regressions but omitted for brevity. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Appendix Table 4.1c1 Quantile regression results: AUS

VARIABLES	(1) 0.25	(2) 0.5	(3) 0.75
lbmi	0.882***	0.949***	0.960***
	(0.0172)	(0.00861)	(0.0142)
finstress1	0.0944	0.0198	0.327
	(0.142)	(0.108)	(0.204)
age	-0.00985	-0.0117**	-0.0161**
	(0.00778)	(0.00501)	(0.00727)
female	-0.107	-0.0270	0.0718
	(0.104)	(0.0725)	(0.125)
yedu	-0.0136	-0.00411	-0.0158
	(0.0117)	(0.00857)	(0.0115)
married	0.122	0.0661	0.307
	(0.197)	(0.151)	(0.203)
widowed	-0.145	-0.103	0.106
	(0.217)	(0.156)	(0.230)
divorced	0.334	0.0801	0.404
	(0.214)	(0.177)	(0.268)
retired	-0.00539	-0.0837	-0.224*
	(0.143)	(0.0963)	(0.135)
hhsize	-0.0369	-0.0845**	-0.172***
	(0.0510)	(0.0344)	(0.0520)
thinc	-0.00827	-0.0293	-0.0180
	(0.0216)	(0.0256)	(0.0303)
hrass	0.00120	0.000312	-0.00262
	(0.00242)	(0.00151)	(0.00207)
gali	0.288**	0.270***	0.360***
	(0.131)	(0.0839)	(0.128)
esmoked	-0.215*	-0.174**	-0.0631
	(0.129)	(0.0804)	(0.130)
phinact	0.303*	0.140	0.127
	(0.176)	(0.157)	(0.253)
foodpc	0.310	0.183	-0.519
	(0.391)	(0.287)	(0.389)
eurod	-0.0636*	-0.0674***	-0.00522
	(0.0340)	(0.0259)	(0.0370)
goodhealth	-0.00501	-0.0107	0.158
	(0.132)	(0.0919)	(0.139)
poorhealth	-0.527	0.251	0.684*
	(0.597)	(0.289)	(0.388)
w3	-0.0129	-0.00347	-0.0512
	(0.159)	(0.117)	(0.190)
w4	0.129	0.163	0.355**
	(0.144)	(0.112)	(0.162)
w5	-0.217	-0.229**	-0.253
	(0.165)	(0.105)	(0.173)
Constant	3.297***	2.585***	3.399***
	(0.727)	(0.522)	(0.709)
Observations	1,532	1,532	1,532
R-squared	0.775	0.776	0.775

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c2 Quantile regression results: DEU

	(1)	(2)	(3)
VARIABLES	0.25	0.5	0.75
lbmi	0.905***	0.975***	0.986***
	(0.0126)	(0.00849)	(0.0114)
finstress1	0.0973	0.0257	0.133
	(0.120)	(0.0682)	(0.128)
age	-0.00626	-0.0102**	-0.0165**
	(0.00649)	(0.00420)	(0.00673)
female	-0.175**	-0.0108	0.0789
	(0.0853)	(0.0517)	(0.0869)
yedu	-0.00259	-0.00970	-0.0194*
	(0.0137)	(0.00716)	(0.0109)
married	0.0896	0.141	-0.571
	(0.146)	(0.176)	(0.352)
widowed	-0.345*	0.0711	-0.574
	(0.195)	(0.179)	(0.382)
divorced	0.102	0.159	-0.455
	(0.229)	(0.187)	(0.401)
retired	0.0774	0.0412	-0.0107
	(0.101)	(0.0656)	(0.112)
hhsize	0.113*	0.0831	-0.0377
	(0.0623)	(0.0568)	(0.0784)
thinc	-0.00625	-0.0216	-0.0306
	(0.0138)	(0.0138)	(0.0295)
hrass	-0.00275	-0.000399	0.000423
	(0.00220)	(0.00128)	(0.00203)
gali	0.0625	0.128**	0.164*
	(0.0971)	(0.0601)	(0.0944)
esmoked	-0.168*	-0.173***	-0.114
	(0.0914)	(0.0603)	(0.0954)
phinact	-0.575***	-0.0824	0.237
	(0.204)	(0.177)	(0.286)
foodpc	0.0209	-0.157	-0.687*
	(0.303)	(0.223)	(0.398)
eurod	-0.0224	-0.0301**	-0.0461
	(0.0232)	(0.0144)	(0.0293)
goodhealth	0.108	-0.0130	-0.102
	(0.111)	(0.0712)	(0.116)
poorhealth	-0.0980	-0.229*	-0.239
	(0.156)	(0.122)	(0.254)
w3	-0.0428	0.0647	0.0652
	(0.132)	(0.0954)	(0.143)
w4	0.312***	0.141*	0.0499
	(0.0916)	(0.0746)	(0.129)
w5	-0.0160	-0.0356	-0.254**
	(0.103)	(0.0725)	(0.129)
Constant	2.112***	1.482***	3.720***
	(0.625)	(0.480)	(0.699)
Observations	2,252	2,252	2,252
R-squared	0.801	0.803	0.802

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c3 Quantile regression results: SWE

VARIABLES	(1) 0.25	(2) 0.5	(3) 0.75
lbmi	0.918***	0.981***	1.001***
	(0.00934)	(0.00441)	(0.00748)
finstress1	-0.0152	0.00252	0.123
	(0.127)	(0.0681)	(0.128)
age	-0.0215***	-0.0110***	-0.00966*
	(0.00511)	(0.00305)	(0.00547)
female	-0.167***	-0.0147	0.111*
	(0.0526)	(0.0340)	(0.0570)
yedu	-0.00406	0.00277	-0.000768
	(0.00758)	(0.00451)	(0.00857)
married	-0.0362	0.138**	0.192
	(0.124)	(0.0631)	(0.135)
widowed	0.0121	0.182**	0.183
	(0.148)	(0.0740)	(0.144)
divorced	-0.196	0.129*	0.236
	(0.153)	(0.0758)	(0.162)
retired	0.0336	-0.0431	-0.142
	(0.0707)	(0.0490)	(0.0907)
hhsize	-0.0801	-0.107***	-0.0784
	(0.0662)	(0.0385)	(0.0554)
thinc	-0.00247	-0.00398	-0.0141
	(0.0102)	(0.00725)	(0.0120)
hrass	0.000696	0.000153	8.35e-06
	(0.00115)	(0.000431)	(0.000746)
gali	0.0832	0.0825**	0.148**
	(0.0610)	(0.0379)	(0.0683)
esmoked	-0.0506	-0.0100	0.0798
	(0.0573)	(0.0375)	(0.0631)
phinact	0.188	0.145	0.254
	(0.249)	(0.116)	(0.193)
foodpc	-0.318	-0.179	0.0237
	(0.226)	(0.160)	(0.238)
eurod	-0.0332*	-0.0177	-0.0208
	(0.0184)	(0.0116)	(0.0223)
goodhealth	-0.113	-0.0907*	-0.296***
	(0.0779)	(0.0488)	(0.0972)
poorhealth	-0.416	-0.121	-0.0547
	(0.280)	(0.105)	(0.158)
w3	-0.0632	-0.0234	0.114
	(0.0895)	(0.0593)	(0.103)
w4	0.0504	0.0242	0.156*
	(0.0699)	(0.0517)	(0.0815)
w5	-0.0764	0.00889	0.0225
	(0.0815)	(0.0513)	(0.0722)
Constant	3.598***	1.523***	1.562***
	(0.505)	(0.280)	(0.494)
Observations	3,320	3,320	3,320
R-squared	0.828	0.828	0.828

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c4 Quantile regression results: ESP

VARIABLES	(1) 0.25	(2) 0.5	(3) 0.75
lbmi	0.719***	0.845***	0.848***
	(0.0263)	(0.0140)	(0.0196)
finstress1	0.0454	0.152	0.344**
	(0.133)	(0.0955)	(0.167)
age	-0.0200**	-0.0112**	-0.00339
	(0.00797)	(0.00514)	(0.0102)
female	-0.280*	-0.120	-0.0319
	(0.156)	(0.106)	(0.214)
yedu	0.00156	-0.0134	-0.0423***
	(0.0123)	(0.00979)	(0.0155)
married	0.282	0.143	-0.0165
	(0.288)	(0.223)	(0.417)
widowed	0.238	0.128	-0.332
	(0.309)	(0.224)	(0.430)
divorced	-0.419	-0.157	-0.264
	(0.662)	(0.282)	(0.514)
retired	-0.0315	-0.0947	-0.268
	(0.142)	(0.105)	(0.184)
hhsize	-0.0465	0.0495	0.0974
	(0.0761)	(0.0471)	(0.0993)
thinc	-0.00613	-0.0230	-0.0355
	(0.0391)	(0.0265)	(0.0517)
hrass	0.00330	0.00226	-0.00153
	(0.00423)	(0.00200)	(0.00247)
gali	0.433***	0.122	0.108
	(0.146)	(0.0975)	(0.180)
esmoked	0.0915	0.0897	-0.161
	(0.154)	(0.101)	(0.192)
phinact	-0.0190	0.230	0.355
	(0.209)	(0.141)	(0.222)
foodpc	-0.336	0.489	1.519**
	(0.444)	(0.378)	(0.732)
eurod	-0.0797***	-0.0489**	0.00527
	(0.0302)	(0.0219)	(0.0332)
goodhealth	-0.0609	-0.0564	0.00908
	(0.147)	(0.104)	(0.169)
poorhealth	-0.263	-0.0165	0.384
	(0.240)	(0.166)	(0.247)
w3	-0.205	-0.180	0.111
	(0.188)	(0.133)	(0.249)
w4	-0.422**	-0.103	0.249
	(0.203)	(0.131)	(0.237)
w5	-0.310	-0.157	-0.0432
	(0.204)	(0.121)	(0.191)
Constant	8.033***	4.913***	5.517***
	(0.985)	(0.602)	(1.221)
Observations	2,876	2,876	2,876
R-squared	0.499	0.503	0.501

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c5 Quantile regression results: ITA

VARIABLES	(1) 0.25	(2) 0.5	(3) 0.75
lbmi	0.843***	0.917***	0.931***
	(0.0126)	(0.00965)	(0.0116)
finstress1	-0.0306	-0.0288	0.134
	(0.0881)	(0.0616)	(0.0882)
age	-0.0219***	-0.0138***	-0.0187***
	(0.00684)	(0.00467)	(0.00680)
female	-0.229***	-0.0954	-0.117
	(0.0877)	(0.0599)	(0.101)
yedu	-0.00686	-0.0173**	-0.0282***
	(0.0126)	(0.00725)	(0.00946)
married	0.182	-0.156	-0.667***
	(0.273)	(0.144)	(0.208)
widowed	0.262	-0.0501	-0.558**
	(0.296)	(0.172)	(0.224)
divorced	0.180	-0.230	-0.177
	(0.319)	(0.187)	(0.364)
retired	0.276***	0.0664	-0.159
	(0.107)	(0.0685)	(0.106)
hhsize	-0.0512	0.0341	-0.00767
	(0.0484)	(0.0309)	(0.0421)
thinc	-0.00439	0.0119	-0.00683
	(0.0217)	(0.0129)	(0.0183)
hrass	0.00213	0.000402	0.000575
	(0.00153)	(0.00141)	(0.00165)
gali	0.00826	0.0871	0.225**
	(0.0804)	(0.0660)	(0.0981)
esmoked	0.0271	-0.0116	-0.0644
	(0.0947)	(0.0642)	(0.103)
phinact	0.0776	0.209**	0.380***
	(0.134)	(0.0899)	(0.127)
foodpc	0.582*	0.329*	0.0305
	(0.324)	(0.195)	(0.278)
eurod	-0.0173	0.00590	-0.00349
	(0.0226)	(0.0144)	(0.0190)
goodhealth	0.0344	-0.0638	-0.123
	(0.0936)	(0.0649)	(0.0996)
poorhealth	-0.377*	-0.143	0.0261
	(0.210)	(0.135)	(0.162)
w3	-0.239**	-0.108	0.0616
	(0.113)	(0.0819)	(0.119)
w4	-0.228**	0.00500	0.158
	(0.114)	(0.0842)	(0.111)
w5	-0.322**	-0.176**	0.138
	(0.132)	(0.0823)	(0.133)
Constant	4.634***	3.309***	4.954***
	(0.716)	(0.499)	(0.702)
Observations	3,744	3,744	3,744
R-squared	0.685	0.689	0.686

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c6 Quantile regression results: FRA

VARIABLES	(1) 0.25	(2) 0.5	(3) 0.75
lbmi	0.905***	0.961***	0.996***
	(0.00776)	(0.00551)	(0.0112)
finstress1	0.0717	0.110*	0.197**
	(0.0877)	(0.0574)	(0.0949)
age	-0.0199***	-0.0159***	-0.0228***
	(0.00498)	(0.00327)	(0.00636)
female	-0.168**	0.0260	0.132
	(0.0719)	(0.0456)	(0.0893)
yedu	-0.00687	-0.00287	-0.0111
	(0.00967)	(0.00531)	(0.00871)
married	0.258**	0.151*	0.175
	(0.116)	(0.0869)	(0.173)
widowed	0.141	0.214**	0.357*
	(0.129)	(0.0936)	(0.205)
divorced	0.185	0.173	0.171
	(0.139)	(0.106)	(0.198)
retired	0.209**	0.135**	-0.00652
	(0.0981)	(0.0612)	(0.109)
hhsize	-0.0410	-0.0124	-0.0903
	(0.0590)	(0.0330)	(0.0613)
thinc	-0.00182	-0.00956	-0.0246*
	(0.0173)	(0.00930)	(0.0127)
hrass	-0.00261*	-0.00140	-0.00124
	(0.00145)	(0.000984)	(0.000909)
gali	-0.0410	0.00957	0.0859
	(0.0798)	(0.0445)	(0.0897)
esmoked	-0.0171	-0.0480	-0.0662
	(0.0749)	(0.0512)	(0.0836)
phinact	0.119	0.107	0.0157
	(0.126)	(0.0740)	(0.195)
foodpc	-0.0310	0.116	0.0233
	(0.144)	(0.109)	(0.205)
eurod	-0.0866***	-0.0429***	-0.0467*
	(0.0204)	(0.0129)	(0.0247)
goodhealth	-0.0542	-0.101*	-0.121
	(0.0953)	(0.0559)	(0.0940)
poorhealth	-0.0666	0.135	0.425**
	(0.202)	(0.120)	(0.186)
w3	-0.0236	0.131*	0.485***
	(0.112)	(0.0713)	(0.130)
w4	0.0561	0.109*	0.367***
	(0.0882)	(0.0584)	(0.105)
w5	0.0149	0.0201	0.102
	(0.0807)	(0.0545)	(0.104)
Constant	3.465***	2.137***	2.609***
	(0.447)	(0.308)	(0.596)
Observations	2,816	2,816	2,816
R-squared	0.815	0.817	0.816

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c7 Quantile regression results: DNK

	(1)	(2)	(3)
VARIABLES	0.25	0.5	0.75
lbmi	0.924***	0.975***	0.996***
	(0.00880)	(0.00622)	(0.00949)
finstress1	0.225*	0.0750	0.0141
	(0.129)	(0.0898)	(0.128)
age	-0.0157***	-0.00863*	-0.0213***
	(0.00551)	(0.00476)	(0.00562)
female	-0.188***	-0.0364	0.00972
	(0.0721)	(0.0482)	(0.0597)
yedu	0.0134	-0.00697	-0.0114
	(0.0141)	(0.00779)	(0.01000)
married	0.213	-0.00898	0.00136
	(0.147)	(0.0841)	(0.113)
widowed	0.371**	0.116	0.396***
	(0.160)	(0.104)	(0.138)
divorced	0.303*	0.211*	0.201
	(0.180)	(0.110)	(0.128)
retired	-0.0515	-0.000505	0.0395
	(0.0911)	(0.0703)	(0.0969)
hhsize	-0.0687	0.00600	-0.00765
	(0.0562)	(0.0478)	(0.0660)
thinc	0.00679	0.00603	0.00631
	(0.0171)	(0.0164)	(0.0203)
hrass	0.00104	0.000700	0.00108
	(0.00120)	(0.000724)	(0.00105)
gali	-0.00319	0.0878	0.160**
	(0.0789)	(0.0591)	(0.0783)
esmoked	0.0637	0.126**	0.213***
	(0.0722)	(0.0534)	(0.0694)
phinact	-0.287	-0.112	0.154
	(0.392)	(0.146)	(0.323)
foodpc	-0.318	-0.0637	-0.243
	(0.268)	(0.194)	(0.282)
eurod	-0.0307	-0.0139	0.0176
	(0.0223)	(0.0177)	(0.0208)
goodhealth	0.0891	0.0147	-0.271**
	(0.136)	(0.0976)	(0.108)
poorhealth	-0.163	-0.266	-0.145
	(0.270)	(0.182)	(0.232)
w3	-0.216**	-0.102	-0.0567
	(0.0982)	(0.0897)	(0.126)
w4	-0.115	-0.0318	-0.202**
	(0.0999)	(0.0730)	(0.0877)
w5	0.0456	0.0201	-0.139
	(0.101)	(0.0687)	(0.103)
Constant	2.204***	1.208***	2.495***
	(0.593)	(0.374)	(0.536)
Observations	2,500	2,500	2,500
R-squared	0.825	0.826	0.824

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c8 Quantile regression results: CHE

	(1)	(2)	(3)
VARIABLES	0.25	0.5	0.75
lbmi	0.923***	0.965***	0.991***
	(0.0151)	(0.00948)	(0.0115)
finstress1	0.0231	-0.0103	0.185
	(0.142)	(0.122)	(0.177)
age	-0.0113	-0.00679	-0.0235***
	(0.00871)	(0.00480)	(0.00702)
female	-0.0336	0.0179	0.194**
	(0.104)	(0.0635)	(0.0900)
yedu	0.00510	-0.0166***	-0.0271***
	(0.0101)	(0.00525)	(0.00979)
married	0.0724	0.0366	-0.255
	(0.170)	(0.154)	(0.237)
widowed	-0.117	-0.0637	-0.0418
	(0.212)	(0.162)	(0.312)
divorced	0.151	0.00625	-0.191
	(0.207)	(0.163)	(0.299)
retired	-0.0102	-0.0633	-0.0606
	(0.122)	(0.0821)	(0.100)
hhsize	-0.128*	-0.0347	-0.0258
	(0.0652)	(0.0408)	(0.0739)
thinc	0.00810	0.00571*	-0.00135
	(0.00560)	(0.00329)	(0.00524)
hrass	0.000302	0.000151	0.000303
	(0.000763)	(0.000488)	(0.000664)
gali	0.149	0.0466	0.222**
	(0.114)	(0.0844)	(0.1000)
esmoked	-0.0545	-0.0398	-0.0292
	(0.0976)	(0.0614)	(0.115)
phinact	0.279	0.339	0.567**
	(0.581)	(0.301)	(0.273)
foodpc	-0.142	-0.00117	-0.125
	(0.207)	(0.144)	(0.207)
eurod	-0.0547*	-0.0475**	-0.0613**
	(0.0304)	(0.0190)	(0.0278)
goodhealth	0.256	0.0834	-0.0108
	(0.227)	(0.117)	(0.142)
poorhealth	0.478	0.107	0.155
	(0.484)	(0.249)	(1.349)
w3	-0.0905	0.0534	0.242
	(0.129)	(0.105)	(0.173)
w4	-0.0279	0.0850	0.272**
	(0.106)	(0.0967)	(0.125)
w5	-0.310*	-0.0658	0.0549
	(0.164)	(0.0900)	(0.128)
Constant	2.253***	1.647***	3.071***
	(0.739)	(0.537)	(0.755)
Observations	1,376	1,376	1,376
R-squared	0.851	0.852	0.851

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix Table 4.1c9 Quantile regression results: BEL

	(1)	(2)	(3)
VARIABLES	0.25	0.5	0.75
lbmi	0.921***	0.969***	0.983***
	(0.00674)	(0.00451)	(0.00668)
finstress1	0.00177	-0.0169	0.0707
	(0.0634)	(0.0402)	(0.0626)
age	-0.0172***	-0.0144***	-0.0207***
	(0.00354)	(0.00232)	(0.00367)
female	-0.0644	0.0690**	0.127**
	(0.0540)	(0.0330)	(0.0541)
yedu	0.000808	-0.00775*	-0.0220***
	(0.00726)	(0.00440)	(0.00629)
married	-0.0795	-0.0722	0.0231
	(0.137)	(0.0748)	(0.118)
widowed	-0.167	-0.0858	0.0719
	(0.152)	(0.0774)	(0.119)
divorced	-0.167	-0.102	0.0298
	(0.154)	(0.0926)	(0.135)
retired	0.101*	0.0880**	-0.00437
	(0.0538)	(0.0369)	(0.0606)
hhsize	-0.0126	0.0257	-0.00347
	(0.0444)	(0.0265)	(0.0406)
thinc	0.00504	-0.00152	-0.00307
	(0.00394)	(0.00235)	(0.00375)
hrass	0.00115	-0.000190	-0.000528
	(0.000902)	(0.000618)	(0.00117)
gali	0.0648	0.0580	0.146**
	(0.0547)	(0.0382)	(0.0574)
esmoked	-0.00869	0.0367	0.120**
	(0.0517)	(0.0354)	(0.0572)
phinact	0.0702	0.169**	0.354***
	(0.108)	(0.0713)	(0.126)
foodpc	0.0943	0.229***	0.00705
	(0.140)	(0.0860)	(0.126)
eurod	-0.0644***	-0.0257***	-0.0179
	(0.0161)	(0.00903)	(0.0134)
goodhealth	0.289***	0.0888*	-0.0639
	(0.0804)	(0.0500)	(0.0692)
poorhealth	-0.111	0.0501	-0.0414
	(0.196)	(0.123)	(0.250)
w3	-0.107	-0.0212	0.181**
	(0.0738)	(0.0511)	(0.0835)
w4	-0.0254	0.0105	0.128**
	(0.0635)	(0.0433)	(0.0646)
w5	-0.0927	-0.0903**	0.0246
	(0.0671)	(0.0403)	(0.0664)
Constant	2.500***	1.745***	2.707***
	(0.399)	(0.249)	(0.384)
Observations	5,368	5,368	5,368
R-squared	0.802	0.804	0.803

Notes: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses. See Table 4.2 for definitions of all variables.

Appendix 4.2 Regressing measured body weight in the HRS

Appendix Table 4.2a Regressing measured body weight using HRS

	(1)	(2)
Dependent variable: Nurse measured body weight	female	male
weight	0.800***	0.649***
	(0.0488)	(0.0745)
weight^2	0.00257***	0.00364***
	(0.000380)	(0.000525)
weight^3	-0.000***	-0.000***
	(0.000)	(0.000)
agedum1	0.0990	0.831
	(0.488)	(0.776)
agedum2	-0.512	0.712
	(0.468)	(0.755)
agedum3	-0.433	0.748
	(0.474)	(0.762)
agedum4	-0.692	0.811
	(0.483)	(0.767)
agedum5	-0.568	0.786
	(0.480)	(0.763)
agedum6	-1.246**	0.878
	(0.493)	(0.773)
agedum7	-1.165**	1.264
	(0.527)	(0.799)
agedum8	-0.978*	0.806
	(0.551)	(0.834)
Constant	6.702***	10.12***
	(1.796)	(3.090)
Observations	18,533	13,223
R-squared	0.679	0.680

Note: *indicates statistical significance at the 10% level; ** at the 5% level; *** at the 1% level. Standard errors are in parentheses.

Appendix Table 4.2b Marginal effects of all regressors on the probability of being obese using corrected body weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUT	DEU	SWE	ESP	ITA	FRA	DNK	CHE	BEL
lobesity	0.134***	0.0865***	0.0953***	0.180***	0.163***	0.162***	0.0975***	0.0861***	0.143***
	(0.0330)	(0.0249)	(0.0195)	(0.0276)	(0.0236)	(0.0267)	(0.0216)	(0.0305)	(0.0179)
intobesity	0.349***	0.348***	0.291***	0.290***	0.283***	0.262***	0.291***	0.240***	0.289***
	(0.0303)	(0.0249)	(0.0196)	(0.0239)	(0.0213)	(0.0279)	(0.0219)	(0.0365)	(0.0172)
finstress1	0.0423*	0.00493	0.0174	0.0225	0.0169	0.0149	0.00165	0.0211	-0.00774
	(0.0252)	(0.0170)	(0.0159)	(0.0163)	(0.0139)	(0.0147)	(0.0198)	(0.0231)	(0.0109)
intfinstress1	0.0175	0.0658***	0.00472	0.0391**	-0.00734	0.0203	0.0126	0.0451*	0.0136
	(0.0295)	(0.0231)	(0.0189)	(0.0198)	(0.0180)	(0.0170)	(0.0220)	(0.0245)	(0.0132)
age	0.0194	0.0371*	-0.00856	-0.0513	0.0287	0.00397	-0.0318	0.0147	-0.00319
	(0.0363)	(0.0224)	(0.0181)	(0.0355)	(0.0520)	(0.0134)	(0.0231)	(0.0250)	(0.0119)
female	-0.0288	-0.0655***	-0.0392***	-0.0792***	-0.0503***	-0.0193	-0.0500***	0.0241	-0.0439***
	(0.0277)	(0.0196)	(0.0139)	(0.0258)	(0.0178)	(0.0161)	(0.0164)	(0.0195)	(0.0129)
yedu	-0.00143	-0.00582*	-0.000860	-0.00420*	-0.00587**	-0.000752	-0.000245	-0.00397**	-0.00296*
	(0.00277)	(0.00297)	(0.00172)	(0.00216)	(0.00228)	(0.00199)	(0.00271)	(0.00187)	(0.00170)
married	-0.0256	-0.256*	0.0648	0.00187	0.0456	0.0578	0.0363	0.121*	-0.285*
	(0.157)	(0.135)	(0.0834)	(0.0585)	(0.0526)	(0.0728)	(0.117)	(0.0656)	(0.161)
widowed	-0.151	-0.338**	0.0982	-0.0514	0.0184	0.0608	-0.0235	0.0588	-0.326**
	(0.163)	(0.142)	(0.0860)	(0.0510)	(0.0416)	(0.0741)	(0.121)	(0.0452)	(0.163)
divorced	0.165	-0.152	0.0288	-0.00120	0.0791	0.0193	0.0874	0.0665	-0.268*
	(0.217)	(0.132)	(0.0949)	(0.129)	(0.121)	(0.0786)	(0.115)	(0.0928)	(0.156)
retired	-0.0283	-0.00868	-0.0222	-0.0162	0.0172	-0.00745	0.0181	0.00808	0.00957
	(0.0254)	(0.0190)	(0.0148)	(0.0209)	(0.0175)	(0.0165)	(0.0169)	(0.0168)	(0.0114)
hhsize	-0.00703	-0.0123	0.00394	0.00979	-0.0140	-0.00987	-0.0103	-0.00446	-0.00354
	(0.0141)	(0.0163)	(0.0135)	(0.0111)	(0.00877)	(0.0121)	(0.0158)	(0.0131)	(0.00919)
thinc	-0.00484	-0.00648*	-0.00512**	-0.00486	0.00382	0.000658	-0.00174	0.000731	0.000900
	(0.00549)	(0.00349)	(0.00220)	(0.00669)	(0.00388)	(0.00307)	(0.00329)	(0.000771)	(0.000702)
hrass	-0.000263	-0.000153	-0.000397*	0.000150	8.46e-05	-3.66e-05	0.000135	0.000112	3.25e-05
	(0.000543)	(0.000388)	(0.000206)	(0.000338)	(0.000337)	(0.000259)	(0.000249)	(0.000109)	(0.000245)
gali	0.0404*	0.0174	0.0241**	0.0174	0.0202	0.0209	0.0350**	-0.00535	0.0395***

	(0.0211)	(0.0155)	(0.0112)	(0.0182)	(0.0138)	(0.0131)	(0.0145)	(0.0164)	(0.00991)
esmoked	0.00117	-0.0465*	-0.0209	-0.00762	-0.0198	-0.0422*	0.0161	-0.0136	0.0329**
	(0.0345)	(0.0251)	(0.0192)	(0.0325)	(0.0234)	(0.0219)	(0.0222)	(0.0262)	(0.0164)
phinact	0.0504	-0.00417	0.0152	0.00981	0.00151	0.0333*	-0.0103	0.0552*	-0.0164
	(0.0323)	(0.0289)	(0.0252)	(0.0214)	(0.0160)	(0.0202)	(0.0303)	(0.0293)	(0.0147)
foodpc	0.0919	0.0962	0.0511	0.192***	-0.0130	0.00269	-0.0208	-0.00615	0.0291
	(0.0792)	(0.0589)	(0.0472)	(0.0684)	(0.0516)	(0.0296)	(0.0493)	(0.0281)	(0.0251)
eurod	-0.00832	0.00309	-0.0100***	-0.00494	-0.00273	-0.00828***	-0.00981**	-0.0102**	-0.00660***
	(0.00536)	(0.00403)	(0.00330)	(0.00346)	(0.00280)	(0.00312)	(0.00411)	(0.00452)	(0.00248)
goodhealth	0.0303	0.00259	-0.00491	-0.0200	-0.0116	-0.0169	-0.000280	-0.0285	0.0104
	(0.0236)	(0.0169)	(0.0132)	(0.0185)	(0.0144)	(0.0146)	(0.0182)	(0.0211)	(0.0117)
poorhealth	0.0158	-0.0449*	-0.0355	0.0148	-0.00494	-0.00969	0.0377	0.0591*	0.00132
	(0.0390)	(0.0261)	(0.0237)	(0.0242)	(0.0198)	(0.0213)	(0.0291)	(0.0337)	(0.0212)
w3	-0.0880	-0.128	0.0427	0.215	-0.136	0.0288	0.112	-0.0605	-0.0178
	(0.159)	(0.101)	(0.0842)	(0.152)	(0.212)	(0.0683)	(0.0997)	(0.117)	(0.0518)
w4	-0.107	-0.232	0.0784	0.320	-0.224	0.00763	0.169	-0.0728	0.00723
	(0.229)	(0.144)	(0.120)	(0.221)	(0.315)	(0.0935)	(0.145)	(0.165)	(0.0748)
w5	-0.145	-0.290	0.0905	0.430	-0.274	-0.0171	0.231	-0.125	0.00266
	(0.301)	(0.189)	(0.156)	(0.292)	(0.419)	(0.120)	(0.192)	(0.215)	(0.0984)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. The dependent variable is corrected *obesity*. Initial values of all time-varying variables are included in all regressions but omitted for brevity. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Appendix Table 4.2c Marginal effects of all regressors on the probability of being overweight using corrected body weight

VARIABLES	(1) AUT	(2) DEU	(3) SWE	(4) ESP	(5) ITA	(6) FRA	(7) DNK	(8) CHE	(9) BEL
loverweight	0.141***	0.101***	0.100***	0.123***	0.109***	0.114***	0.132***	0.114***	0.158***
	(0.0337)	(0.0246)	(0.0212)	(0.0244)	(0.0202)	(0.0233)	(0.0263)	(0.0349)	(0.0191)
intoverweight	0.276***	0.298***	0.320***	0.218***	0.305***	0.315***	0.311***	0.333***	0.257***
	(0.0328)	(0.0238)	(0.0208)	(0.0209)	(0.0181)	(0.0220)	(0.0255)	(0.0349)	(0.0190)
finstress1	-0.0288	0.0414**	-0.00553	0.0146	-0.00993	-0.00470	0.0256	-0.0208	-0.00796
	(0.0214)	(0.0199)	(0.0179)	(0.0133)	(0.0126)	(0.0157)	(0.0232)	(0.0277)	(0.0112)
intfinstress1	0.0175	0.0269	-0.00851	0.0187	-0.0456***	0.0388**	0.0184	0.0843**	0.0152
	(0.0241)	(0.0249)	(0.0187)	(0.0151)	(0.0175)	(0.0197)	(0.0259)	(0.0341)	(0.0131)
age	-0.00593	0.0473**	0.00694	-0.0129	-0.00794	-0.00903	0.0183	-0.0281	-0.00859
	(0.0330)	(0.0225)	(0.0190)	(0.0310)	(0.0427)	(0.0146)	(0.0267)	(0.0303)	(0.0136)
female	-0.0464*	-0.0874***	-0.0403***	-0.0686***	-0.0778***	-0.0628***	-0.0733***	-0.0715***	-0.0621***
	(0.0252)	(0.0211)	(0.0143)	(0.0205)	(0.0176)	(0.0186)	(0.0182)	(0.0251)	(0.0134)
yedu	-0.00253	-0.00303	-0.00142	-0.00289*	-0.00723***	-0.00235	0.00153	-0.00845***	-0.00199
	(0.00236)	(0.00279)	(0.00170)	(0.00163)	(0.00213)	(0.00228)	(0.00286)	(0.00262)	(0.00162)
married	0.00469	0.206	0.0674	-0.0694	-0.0417	0.0485	-0.0634	-0.108	0.121
	(0.174)	(0.147)	(0.135)	(0.0455)	(0.0484)	(0.0989)	(0.148)	(0.0704)	(0.207)
widowed	-0.0788	0.243	0.0705	-0.0410	-0.0286	0.0325	-0.0988	-0.121**	0.0377
	(0.178)	(0.151)	(0.137)	(0.0398)	(0.0396)	(0.100)	(0.150)	(0.0562)	(0.208)
divorced	0.0150	0.114	0.0734	-0.0720	-0.0791	0.0319	-0.102	0.0309	0.0421
	(0.248)	(0.166)	(0.144)	(0.0930)	(0.115)	(0.115)	(0.147)	(0.122)	(0.204)
retired	-0.0284	0.0223	0.00622	0.0146	0.0285*	0.0282*	-0.0262	0.00175	0.0235**
	(0.0226)	(0.0196)	(0.0158)	(0.0163)	(0.0156)	(0.0171)	(0.0193)	(0.0207)	(0.0116)
hhsize	-0.0235*	-0.00342	0.00633	0.0139	-0.0216**	0.0111	0.00271	0.00569	-0.00965
	(0.0121)	(0.0154)	(0.0132)	(0.00907)	(0.00852)	(0.0134)	(0.0170)	(0.0162)	(0.00958)
thinc	0.00130	0.00462	-0.00222	0.00180	0.00104	-0.00163	0.00122	-0.000266	3.56e-05
	(0.00506)	(0.00317)	(0.00235)	(0.00530)	(0.00346)	(0.00314)	(0.00372)	(0.00108)	(0.000746)
hrass	-0.000371	-0.000157	0.000250	5.39e-05	0.000243	-0.000503**	-0.000209	-0.000109	-0.000122
	(0.000461)	(0.000380)	(0.000197)	(0.000272)	(0.000308)	(0.000249)	(0.000259)	(0.000127)	(0.000248)
gali	0.0104	-0.0112	0.0262**	0.0262*	-0.000386	0.0216	0.0198	0.00355	0.0221**

	(0.0195)	(0.0164)	(0.0122)	(0.0154)	(0.0127)	(0.0145)	(0.0166)	(0.0199)	(0.00996)
esmoked	0.00361	-0.0249	-0.00837	0.0284	0.0266	-0.0230	-0.0318	-0.00337	0.0335**
	(0.0332)	(0.0264)	(0.0202)	(0.0275)	(0.0213)	(0.0224)	(0.0254)	(0.0326)	(0.0166)
phinact	-0.00426	-0.0573**	0.000215	0.00480	-0.00894	-0.0151	-0.0234	-0.0115	0.00131
	(0.0287)	(0.0289)	(0.0297)	(0.0174)	(0.0145)	(0.0228)	(0.0328)	(0.0465)	(0.0156)
foodpc	-0.0774	-0.0317	0.0799	0.0258	0.0139	0.0299	-0.0761	-0.0209	0.0486*
	(0.0679)	(0.0587)	(0.0514)	(0.0555)	(0.0472)	(0.0308)	(0.0554)	(0.0337)	(0.0258)
eurod	-0.0108**	-0.0112***	0.000210	-0.0109***	0.00368	-0.00896***	-0.00690	-0.00344	-0.00317
	(0.00470)	(0.00423)	(0.00342)	(0.00272)	(0.00260)	(0.00320)	(0.00430)	(0.00550)	(0.00246)
goodhealth	0.00807	0.00685	0.00949	-0.0137	-0.00937	-0.0118	-0.0128	0.0301	-0.00452
	(0.0217)	(0.0185)	(0.0145)	(0.0157)	(0.0134)	(0.0157)	(0.0205)	(0.0276)	(0.0121)
poorhealth	-0.0421	-0.0275	0.0278	-0.0285	-0.0420**	-0.0408*	-0.0548*	0.101	-0.0491**
	(0.0320)	(0.0283)	(0.0289)	(0.0196)	(0.0189)	(0.0242)	(0.0323)	(0.0792)	(0.0232)
w3	-0.00741	-0.192*	-0.00403	0.0327	-0.0159	0.0448	-0.0535	0.114	-0.00380
	(0.146)	(0.103)	(0.0874)	(0.132)	(0.175)	(0.0740)	(0.115)	(0.140)	(0.0592)
w4	0.0563	-0.270*	-0.0304	0.0656	0.0372	0.0749	-0.117	0.200	0.0341
	(0.210)	(0.145)	(0.124)	(0.192)	(0.259)	(0.102)	(0.168)	(0.199)	(0.0855)
w5	0.0131	-0.385**	-0.0649	0.0716	0.0250	0.100	-0.154	0.233	0.0467
	(0.275)	(0.190)	(0.162)	(0.254)	(0.345)	(0.131)	(0.222)	(0.260)	(0.113)
Observations	1,532	2,252	3,320	2,876	3,744	2,816	2,500	1,376	5,368

Notes: All regressions are estimated using a RE probit model. The dependent variable is corrected *overweight*. Initial values of all time-varying variables are included in all regressions but omitted for brevity. Wave dummies are included in all regressions. Standard errors are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% level respectively. See Table 4.2 for complete definitions of all variables.

Chapter Five: Conclusion

5.1. Summary of the findings

This thesis consists of three empirical studies on household finance using micro-level data from China and nine EU countries. In particular, I investigate the determinants of financial inclusion and the impact of financial inclusion on household consumption in China, the consumption responses to health shocks in China, and the association between financial stress and body weight in nine EU countries. This thesis contributes to the existing literature by providing empirical evidence on several heated topics.

In Chapter Two, using the 2013 wave of the China Household Finance Survey which consists of 28,100 households from 29 Chinese provinces/municipalities, I study the determinants of financial inclusion in China, with focus on the relationship between informal and formal finance. Different from Allen et al. (2018) who find informal and formal finance are both complements and substitutes at the firm-level, I only find evidence of a negative association between the use of informal finance and having bank accounts, credit cards, bank loans and the overall financial inclusion among Chinese households. This negative association remains significant after I control for the endogeneity of informal finance. Moreover, I find a strongly positive association between financial inclusion and household non-durable consumption. These findings indicate that enhancing financial inclusion may be a valid tool for boosting domestic consumption in China.

In Chapter Three, using the 2011, 2013 and 2015 waves of the China Health and Retirement Longitudinal Study, I investigate the extent to which households' consumption profile changes after health shocks. I find that health shocks are significantly associated with increases in out-of-pocket medical expenditure, but not with other non-medical expenditures. The increase in out-of-pocket medical expenditure after health shocks is higher for the urban and poorer residents, as well as for respondents living in provinces with a better healthcare system. These findings suggest that non-medical consumption is generally insured against health shocks in China.

In Chapter Four, I estimate the association between financial stress and the probability of being obese/overweight using data from the Survey of Health, Ageing and Retirement in Europe over the period 2004-2015. After controlling for the state dependence of body weight as well as for individual heterogeneity, I find little evidence of such an association in the sampled countries. In some countries, the association is statistically significant, but the magnitude of the effect is small. I find some evidence for a positive link between financial stress and body weight in Austria, Germany, Sweden, Spain, Italy, France and Switzerland. This link is robust to correcting self-reported weight measures in Austria, Germany and Spain, and to using an objective financial stress measure in Germany and Spain. I also find that the estimated marginal effect of subjective financial stress is more significant and generally larger than that of objective financial stress. This indicates that the subjective perception of financial difficulties may be the mediator of linking financial stress and body weight.

5.2. Policy implications

This thesis provides the following policy implications. Chapter Two documents a negative association between informal finance and financial inclusion among Chinese households. This suggests that borrowing through informal sources is a substitute for formal financial services. Thus, policies aiming at improving the availability and accessibility of formal financial services may reduce the reliance of informal borrowings among Chinese households and ultimately lead to higher domestic consumption. In addition, as I find a positive association between financial inclusion and household total consumption, policies aiming at improving financial inclusion may boost domestic consumption and ultimately stimulate growth in the Chinese economy.

In Chapter Three, I find health shocks are associated with an 8.1-19.1 percent increase in OOP medical expenditure for Chinese individuals aged 45 and over. In addition, I do not find evidence for associations between health shocks and non-medical expenditure. This finding may be the result from underutilisation of healthcare services. In particular, individuals living in rural areas and/or provinces with an underdeveloped healthcare system are more likely to underutilise healthcare services. To eliminate inequality in healthcare utilisation, policy makers should deepen the coverage of public health insurance schemes and make medical services more affordable for the disadvantaged groups such as the poor, residents living in rural areas and in provinces with a less developed healthcare system. In addition, further improvements of healthcare facilities in underdeveloped provinces will also improve healthcare equality in China and boost the usage of healthcare services for those disadvantaged group.

In Chapter Four, I find some evidence for a positive link between financial stress and body weight in Austria, Germany, Sweden, Spain, Italy, France and Switzerland. This link is robust to correcting self-reported weight measures in Austria, Germany and Spain, and to using an alternative financial stress measure in Germany and Spain. In addition, I find that, compared to objective financial stress, subjective financial stress is more likely to be significantly associated with a higher probability of being obese/overweight. These findings suggest that policies targeted at improving citizens’ financial stress coping strategies and confidence in managing financial stress may contribute to lowering the incidence of obesity in Europe especially in Germany and Spain.

5.3. Suggestions for future research

Regarding Chapter Two, further research could look into instrumenting the potentially endogenous household income /wealth. This issue could be solved once community level data and/or more waves of CHFS become available. Furthermore, as only associations are identified due to the cross-sectional data structure, future research could look into establishing causal relationships. In addition, it is worth studying the depth of using financial services other than the simple coverage of these financials services.

In Chapter Three, I only investigate the immediate change of household consumption because the longitudinal data I use only consists of three waves. Future research could focus on estimating the longer-run effect of health shocks. This could be done by estimating a dynamic model after more follow-up waves of CHARLS are published. Additionally, future research could study households' coping strategies following health shocks, such as dissaving, formal and informal borrowing, selling assets, and family transfers. This could help us understand why households' expenditure on non-medical items remains unchanged after a health shock despite the wide but shallow coverage of public health insurance schemes in China.

In Chapter Four, the country level differences in finance-weight nexus are presented but I could not provide readers with sufficient explanations for the differences. Hence, future work should be directed to interpreting differences among sampled countries, and in particular in understanding why the association between financial stress and body weight is significant in some countries but not in others. In addition, the present study only looks at nine EU countries due to the fact that only these nine countries can be tracked from the initial wave to the recent wave of SHARE. Future research could incorporate more countries in the analysis once the longitudinal structure of SHARE is further extended. Finally, for the countries where a significant association between financial stress and body weight is established, investigations on possible mediators or moderators of such a relationship could be conducted in the future.

Reference

Adams, T. & Moore, M. 2007. High-risk health and credit behavior among 18-to 25-year-old college students. *Journal of American College Health,* 56**,** 101-108.

Aguiar, M. & Hurst, E. 2005. Consumption versus expenditure. *Journal of political Economy,* 113**,** 919-948.

Alam, K. & Mahal, A. 2014. Economic impacts of health shocks on households in low and middle income countries: A review of the literature. *Globalization and health,* 10**,** 21.

Allen, F., Carletti, E., Cull, R., Qian, J., Senbet, L. & Valenzuela, P. 2013. *Resolving the african financial development gap: Cross-country comparisons and a within-country study of kenya,* The World Bank.

Allen, F., Demirguc-Kunt, A., Klapper, L. & Peria, M. S. M. 2012. The foundations of financial inclusion: Understanding ownership and use of formal accounts. The World Bank.

Allen, F., Qian, J. & Qian, M. 2005. Law, finance, and economic growth in china. *Journal of financial economics,* 77**,** 57-116.

Allen, F., Qian, M. & Xie, J. 2018. Understanding informal financing.

Andresen, E. M., Malmgren, J. A., Carter, W. B. & Patrick, D. L. 1994. Screening for depression in well older adults: Evaluation of a short form of the ces-d. *American journal of preventive medicine,* 10**,** 77-84.

Asfaw, A. & Braun, J. V. 2004. Is consumption insured against illness? Evidence on vulnerability of households to health shocks in rural ethiopia. *Economic Development and Cultural Change,* 53**,** 115-129.

Averett, S. L. & Smith, J. K. 2014. Financial hardship and obesity. *Economics & Human Biology,* 15**,** 201-212.

Ayyagari, M., Demirgüç-Kunt, A. & Maksimovic, V. 2010. Formal versus informal finance: Evidence from china. *The Review of Financial Studies,* 23**,** 3048-3097.

Babiarz, P., Widdows, R. & Yilmazer, T. 2013. Borrowing to cope with adverse health events: Liquidity constraints, insurance coverage, and unsecured debt. *Health economics,* 22**,** 1177-1198.

Babiarz, P. & Yilmazer, T. 2017. The impact of adverse health events on consumption: Understanding the mediating effect of income transfers, wealth, and health insurance. *Health Economics*.

Baker, M., Stabile, M. & Deri, C. 2004. What do self-reported, objective, measures of health measure? *Journal of human Resources,* 39**,** 1067-1093.

Barber, R. M., Fullman, N., Sorensen, R. J., Bollyky, T., Mckee, M., Nolte, E., Abajobir, A. A., Abate, K. H., Abbafati, C. & Abbas, K. M. 2017. Healthcare access and quality index based on mortality from causes amenable to personal health care in 195 countries and territories, 1990–2015: A novel analysis from the global burden of disease study 2015. *The Lancet,* 390**,** 231-266.

Barnett, M. S. & Brooks, M. R. 2010. *China: Does government health and education spending boost consumption?,* International Monetary Fund.

Baum, C. L. 2009. The effects of cigarette costs on bmi and obesity. *Health Economics,* 18**,** 3-19.

Baum, C. L. & Chou, S.-Y. 2011. The socio-economic causes of obesity. National Bureau of Economic Research.

Beck, T. & Brown, M. 2011. Use of banking services in emerging markets: Household-level evidence. *European Banking Centre Discussion Paper,* 2011-024.

Beck, T., Demirgüç-Kunt, A. & Levine, R. 2007a. Finance, inequality and the poor. *Journal of economic growth,* 12**,** 27-49.

Beck, T., Demirguc-Kunt, A. & Martinez Peria, M. S. 2007b. Reaching out: Access to and use of banking services across countries. *Journal of Financial Economics,* 85**,** 234-266.

Becker, G. S. 1965. A theory of the allocation of time. *The economic journal***,** 493-517.

Behr, A., Bellgardt, E. & Rendtel, U. 2005. Extent and determinants of panel attrition in the european community household panel. *European Sociological Review,* 21**,** 489-512.

Benson, R., Von Hippel, P. T. & Lynch, J. L. 2017. Does more education cause lower bmi, or do lower-bmi individuals become more educated? Evidence from the national longitudinal survey of youth 1979. *Social Science & Medicine*.

Berger, L. M., Hill, J. & Waldfogel, J. 2005. Maternity leave, early maternal employment and child health and development in the us. *The Economic Journal,* 115**,** F29-F47.

Borghans, L. & Golsteyn, B. H. 2006. Time discounting and the body mass index: Evidence from the netherlands. *Economics & Human Biology,* 4**,** 39-61.

Börsch-Supan, A., Hank, K. & Jürges, H. 2005. A new comprehensive and international view on ageing: Introducing the ‘survey of health, ageing and retirement in europe’. *European Journal of Ageing,* 2**,** 245-253.

Bound, J. 1989. Self-reported vs. Objective measures of health in retirement models. National Bureau of Economic Research.

Bridges, S. & Disney, R. 2010. Debt and depression. *Journal of health economics,* 29**,** 388-403.

Bruhn, M. & Love, I. 2014. The real impact of improved access to finance: Evidence from mexico. *The Journal of Finance,* 69**,** 1347-1376.

Brune, L., Giné, X., Goldberg, J. & Yang, D. 2011. *Commitments to save: A field experiment in rural malawi,* The World Bank.

Burgess, R. & Pande, R. 2005. Do rural banks matter? Evidence from the indian social banking experiment. *American Economic Review,* 95**,** 780-795.

Burkhauser, R. V. & Cawley, J. 2008. Beyond bmi: The value of more accurate measures of fatness and obesity in social science research. *Journal of Health Economics,* 27**,** 519-529.

Caliendo, M. & Kopeinig, S. 2005. Some practical guidance for the implementation of propensity score matching. Bonn, germany. *Institute for the Study of Labor, Discussion Paper,(1588).*

Cawley, J., Maclean, J. C. & Kessler, A. S. 2017. Reporting error in weight and height among older adults: Implications for estimating healthcare costs. *The Journal of the Economics of Ageing,* 9**,** 122-144.

Cawley, J., Moran, J. & Simon, K. 2010. The impact of income on the weight of elderly americans. *Health Economics,* 19**,** 979-993.

Centers for Disease Control and Prevention. 2018. *Behaviour, environment, and genetic factors all have a role in causing people to be overweight and obese* [Online]. Available: https://www.cdc.gov/genomics/resources/diseases/obesity/index.htm [Accessed].

Chou, S.-Y., Grossman, M. & Saffer, H. 2004. An economic analysis of adult obesity: Results from the behavioral risk factor surveillance system. *Journal of health economics,* 23**,** 565-587.

Clark, A. & Etilé, F. 2002. Do health changes affect smoking? Evidence from british panel data. *Journal of health economics,* 21**,** 533-562.

Clayton, M., Liñares-Zegarra, J. & Wilson, J. O. 2015. Does debt affect health? Cross country evidence on the debt-health nexus. *Social science & medicine,* 130**,** 51-58.

Conklin, A. I., Forouhi, N. G., Suhrcke, M., Surtees, P., Wareham, N. J. & Monsivais, P. 2013. Socioeconomic status, financial hardship and measured obesity in older adults: A cross-sectional study of the epic-norfolk cohort. *BMC Public Health,* 13**,** 1039.

Courtemanche, C., Heutel, G. & Mcalvanah, P. 2015. Impatience, incentives and obesity. *The Economic Journal,* 125**,** 1-31.

Cull, R., Gan, L., Gao, N. & Xu, L. C. 2015a. Dual credit markets and household access to finance.

Cull, R., Gan, L., Gao, N. & Xu, L. C. 2016. *Social capital, finance, and consumption: Evidence from a representative sample of chinese households*, The World Bank.

Cull, R., Li, W., Sun, B. & Xu, L. C. 2015b. Government connections and financial constraints: Evidence from a large representative sample of chinese firms. *Journal of Corporate Finance,* 32**,** 271-294.

Cutler, D. M., Glaeser, E. L. & Shapiro, J. M. 2003. Why have americans become more obese? *Journal of Economic perspectives,* 17**,** 93-118.

Cutler, D. M. & Lleras-Muney, A. 2010. Understanding differences in health behaviors by education. *Journal of Health Economics,* 29**,** 1-28.

Dallman, M. F., Pecoraro, N., Akana, S. F., La Fleur, S. E., Gomez, F., Houshyar, H., Bell, M., Bhatnagar, S., Laugero, K. D. & Manalo, S. 2003. Chronic stress and obesity: A new view of "comfort food". *Proceedings of the National Academy of Sciences,* 100**,** 11696-11701.

Danø, A. M. 2005. Road injuries and long-run effects on income and employment. *Health economics,* 14**,** 955-970.

Daouli, J., Davillas, A., Demoussis, M. & Giannakopoulos, N. 2014. Obesity persistence and duration dependence: Evidence from a cohort of us adults (1985–2010). *Economics & Human Biology,* 12**,** 30-44.

Deaton, A. 1992. *Understanding consumption*, Oxford University Press.

Decker, S. & Schmitz, H. 2016. Health shocks and risk aversion. *Journal of Health Economics,* 50**,** 156-170.

Degryse, H., Lu, L. & Ongena, S. 2016. Informal or formal financing? Evidence on the co-funding of chinese firms. *Journal of Financial Intermediation,* 27**,** 31-50.

Demirgüç-Kunt, A., Honohan, P. & Beck, T. 2008. *Finance for all?: Policies and pitfalls in expanding access*, World bank.

Demirgüç-Kunt, A. & Klapper, L. 2012. Measuring financial inclusion: The global findex database'. World bank policy research working paper 6025. Washington, dc: World bank.

Demirgüç-Kunt, A. & Klapper, L. 2013. Measuring financial inclusion: Explaining variation in use of financial services across and within countries. *Brookings Papers on Economic Activity,* 2013**,** 279-340.

Disney, R., Emmerson, C. & Wakefield, M. 2006. Ill health and retirement in britain: A panel data-based analysis. *Journal of health economics,* 25**,** 621-649.

Dong, Y. & Lewbel, A. 2015. A simple estimator for binary choice models with endogenous regressors. *Econometric Reviews,* 34**,** 82-105.

Drentea, P. & Lavrakas, P. J. 2000. Over the limit: The association among health, race and debt. *Social science & medicine,* 50**,** 517-529.

Drewnowski, A. & Darmon, N. 2005. The economics of obesity: Dietary energy density and energy cost–. *The American journal of clinical nutrition,* 82**,** 265S-273S.

Eid, J., Overman, H. G., Puga, D. & Turner, M. A. 2008. Fat city: Questioning the relationship between urban sprawl and obesity. *Journal of Urban Economics,* 63**,** 385-404.

Engelhardt, G. V. 1996. Consumption, down payments, and liquidity constraints. *Journal of money, credit and Banking,* 28**,** 255-271.

Eu Statistics on Income and Living Conditions 2016. Eu statistics on income and living conditions,. *In:* INSTITUTE, E. U. (ed.).

Fang, K., Jiang, Y., Shia, B. & Ma, S. 2012. Impact of illness and medical expenditure on household consumptions: A survey in western china. *PLoS One,* 7**,** e52928.

Fang, P., Dong, S., Xiao, J., Liu, C., Feng, X. & Wang, Y. 2010. Regional inequality in health and its determinants: Evidence from china. *Health Policy,* 94**,** 14-25.

Feng, J., He, L. & Sato, H. 2011. Public pension and household saving: Evidence from urban china. *Journal of Comparative Economics,* 39**,** 470-485.

Finkelstein, E. A., Ruhm, C. J. & Kosa, K. M. 2005. Economic causes and consequences of obesity. *Annu. Rev. Public Health,* 26**,** 239-257.

Friedman, M. 1957. The permanent income hypothesis. *A theory of the consumption function.* Princeton University Press.

Fullman, N., Yearwood, J., Abay, S. M., Abbafati, C., Abd-Allah, F., Abdela, J., Abdelalim, A., Abebe, Z., Abebo, T. A. & Aboyans, V. 2018. Measuring performance on the healthcare access and quality index for 195 countries and territories and selected subnational locations: A systematic analysis from the global burden of disease study 2016. *The Lancet,* 391**,** 2236-2271.

Fungáčová, Z. & Weill, L. 2015. Understanding financial inclusion in china. *China Economic Review,* 34**,** 196-206.

García-Gómez, P. 2011. Institutions, health shocks and labour market outcomes across europe. *Journal of health economics,* 30**,** 200-213.

García-Gómez, P., Van Kippersluis, H., O'donnell, O. & Van Doorslaer, E. 2013. Long-term and spillover effects of health shocks on employment and income. *Journal of Human Resources,* 48**,** 873-909.

García Gómez, P. & López Nicolás, Á. 2006. Health shocks, employment and income in the spanish labour market. *Health economics,* 15**,** 997-1009.

Garcia, R., Lusardi, A. & Ng, S. 1997. Excess sensitivity and asymmetries in consumption: An empirical investigation. *Journal of Money, Credit, and Banking***,** 154-176.

Genoni, M. E. 2012. Health shocks and consumption smoothing: Evidence from indonesia. *Economic Development and Cultural Change,* 60**,** 475-506.

Gertler, P. & Gruber, J. 2002. Insuring consumption against illness. *The American Economic Review,* 92**,** 51-70.

Gertler, P., Levine, D. I. & Moretti, E. 2009. Do microfinance programs help families insure consumption against illness? *Health economics,* 18**,** 257-273.

Godard, M. 2016. Gaining weight through retirement? Results from the share survey. *Journal of health economics,* 45**,** 27-46.

Goldsmith, R. W. 1969. Financial structure and development.

Gruber, J. & Frakes, M. 2006. Does falling smoking lead to rising obesity? *Journal of health economics,* 25**,** 183-197.

Guariglia, A., Liu, X. & Song, L. 2011. Internal finance and growth: Microeconometric evidence on chinese firms. *Journal of Development Economics,* 96**,** 79-94.

Guariglia, A. & Mateut, S. 2016. External finance and trade credit extension in china: Does political affiliation make a difference? *The European Journal of Finance,* 22**,** 319-344.

Guariglia, A., Monahan, M., Pickering, K. & Roberts, T. E. 2018. Disentangling the link between financial health and obesity among 50s in england. *Mimeograph,* University of Birmingham.

Guariglia, A. & Poncet, S. 2008. Could financial distortions be no impediment to economic growth after all? Evidence from china. *Journal of Comparative Economics,* 36**,** 633-657.

Guerra, F., Stringhini, S., Vollenweider, P., Waeber, G. & Marques-Vidal, P. 2015. Socio-demographic and behavioural determinants of weight gain in the swiss population. *BMC Public Health,* 15.

Guiso, L. & Sodini, P. 2013. Household finance: An emerging field. *Handbook of the economics of finance.* Elsevier.

Gustavson, K., Von Soest, T., Karevold, E. & Røysamb, E. 2012. Attrition and generalizability in longitudinal studies: Findings from a 15-year population-based study and a monte carlo simulation study. *BMC Public Health,* 12**,** 918.

Hagan, R., Jones, A. M. & Rice, N. 2008. Health shocks and the hazard rate of early retirement in the echp. *Swiss Journal of Economics and Statistics (SJES),* 144**,** 323-335.

Hall, R. E. & Mishkin, F. S. 1980. The sensitivity of consumption to transitory income: Estimates from panel data on households. National Bureau of Economic Research Cambridge, Mass., USA.

He, H., Huang, F., Liu, Z. & Zhu, D. 2018. Breaking the "iron rice bowl:" evidence of precautionary savings from the chinese state-owned enterprises reform. *Journal of Monetary Economics,* 94**,** 94-113.

Hernández-Quevedo, C., Jones, A. M. & Rice, N. 2008. Persistence in health limitations: A european comparative analysis. *Journal of Health Economics,* 27**,** 1472-1488.

Hojman, D. A., Miranda, Á. & Ruiz-Tagle, J. 2016. Debt trajectories and mental health. *Social Science and Medicine,* 167**,** 54-62.

Honohan, P. 2004. Financial development, growth and poverty: How close are the links? *In:* GOODHART, C. A. E. (ed.) *Financial development and economic growth: Explaining the links.* London: Palgrave Macmillan UK.

Honohan, P. 2008. Cross-country variation in household access to financial services. *Journal of Banking & Finance,* 32**,** 2493-2500.

Hunt, A. & Ferguson, J. 2014. Health costs in the european union: How much is related to edcs. *Brussels: The Health and Environmental Alliance*.

Ikeda, S., Kang, M.-I. & Ohtake, F. 2010. Hyperbolic discounting, the sign effect, and the body mass index. *Journal of health economics,* 29**,** 268-284.

Imbens, G. & Wooldridge, J. 2007. *"What's new in econometrics" lecture 5*, NBER.

Islam, A. & Maitra, P. 2012. Health shocks and consumption smoothing in rural households: Does microcredit have a role to play? *Journal of development economics,* 97**,** 232-243.

Jappelli, T. 1990. Who is credit constrained in the u. S. Economy? *The Quarterly Journal of Economics,* 105**,** 219-234.

Jappelli, T. & Pagano, M. 1989. Consumption and capital market imperfections: An international comparison. *The American Economic Review,* 79**,** 1088-1105.

Jappelli, T., Pischke, J., Xf, Rn, S. & Souleles, N. S. 1998. Testing for liquidity constraints in euler equations with complementary data sources. *The Review of Economics and Statistics,* 80**,** 251-262.

Jones, A. M., Koolman, X. & Rice, N. 2006. Health-related non-response in the british household panel survey and european community household panel: Using inverse-probability-weighted estimators in non-linear models. *Journal of the Royal Statistical Society: Series A (Statistics in Society),* 169**,** 543-569.

Jones, A. M., Rice, N. & Zantomio, F. 2016. Acute health shocks and labour market outcomes.

Kandiah, J., Yake, M., Jones, J. & Meyer, M. 2006. Stress influences appetite and comfort food preferences in college women. *Nutrition Research,* 26**,** 118-123.

Kang, M.-I. & Ikeda, S. 2016. Time discounting, present biases, and health-related behaviors: Evidence from japan. *Economics & Human Biology,* 21**,** 122-136.

Keese, M. & Schmitz, H. 2014. Broke, ill, and obese: Is there an effect of household debt on health? *Review of Income and Wealth,* 60**,** 525-541.

Koenker, R. & Bassett Jr, G. 1978. Regression quantiles. *Econometrica: journal of the Econometric Society***,** 33-50.

Koltai, J., Bierman, A. & Schieman, S. 2018. Financial circumstances, mastery, and mental health: Taking unobserved time-stable influences into account. *Social Science & Medicine,* 202**,** 108-116.

Komlos, J., Smith, P. K. & Bogin, B. 2004. Obesity and the rate of time preference: Is there a connection? *Journal of biosocial science,* 36**,** 209-219.

Kruk, M. E., Goldmann, E. & Galea, S. 2009. Borrowing and selling to pay for health care in low-and middle-income countries. *Health Affairs,* 28**,** 1056-1066.

Kumara, A. S. & Samaratunge, R. 2017. Impact of ill-health on household consumption in sri lanka: Evidence from household survey data. *Social Science & Medicine,* 195**,** 68-76.

Lakdawalla, D. & Philipson, T. 2009. The growth of obesity and technological change. *Economics & Human Biology,* 7**,** 283-293.

Levine, R. 1997. Financial development and economic growth: Views and agenda. *Journal of Economic Literature,* 35**,** 688-726.

Lewbel, A. 2000. Semiparametric qualitative response model estimation with unknown heteroscedasticity or instrumental variables. *Journal of Econometrics,* 97**,** 145-177.

Li, C., Lin, L. & Gan, C. E. C. 2016. China credit constraints and rural households' consumption expenditure. *Finance Research Letters,* 19**,** 158-164.

Li, L. 2018. Financial inclusion and poverty: The role of relative income. *China economic Review*.

Li, R., Li, Q., Huang, S. & Zhu, X. 2013. The credit rationing of chinese rural households and its welfare loss: An investigation based on panel data. *China Economic Review,* 26**,** 17-27.

Li, Y., Wu, Q., Liu, C., Kang, Z., Xie, X., Yin, H., Jiao, M., Liu, G., Hao, Y. & Ning, N. 2014. Catastrophic health expenditure and rural household impoverishment in china: What role does the new cooperative health insurance scheme play? *Plos one,* 9**,** e93253.

Liang, L. & Langenbrunner, J. C. 2013. The long march to universal coverage: Lessons from china.

Lindelow, M. & Wagstaff, A. 2005. Health shocks in china: Are the poor and uninsured less protected?

Liu, H. & Guo, G. 2015. Lifetime socioeconomic status, historical context, and genetic inheritance in shaping body mass in middle and late adulthood. *American Sociological Review,* 80**,** 705-737.

Liu, K. 2016. Insuring against health shocks: Health insurance and household choices. *Journal of Health Economis,* 46**,** 16-32.

Liu, Y., Hsiao, W. C. & Eggleston, K. 1999. Equity in health and health care: The chinese experience. *Social Science & Medicine,* 49**,** 1349-1356.

Ljungvall, Å. & Gerdtham, U.-G. 2010. More equal but heavier: A longitudinal analysis of income-related obesity inequalities in an adult swedish cohort. *Social Science & Medicine,* 70**,** 221-231.

Meng, X. 2003. Unemployment, consumption smoothing, and precautionary saving in urban china. *Journal of Comparative Economics,* 31**,** 465-485.

Mialou, A., Amidzic, G. & Massara, A. 2017. Assessing countries' financial inclusion standing—a new composite index. *Journal of Banking and Financial Economics*.

Millán-Calenti, J. C., Tubío, J., Pita-Fernández, S., González-Abraldes, I., Lorenzo, T., Fernández-Arruty, T. & Maseda, A. 2010. Prevalence of functional disability in activities of daily living (adl), instrumental activities of daily living (iadl) and associated factors, as predictors of morbidity and mortality. *Archives of gerontology and geriatrics,* 50**,** 306-310.

Mitra, S., Palmer, M., Mont, D. & Groce, N. 2016. Can households cope with health shocks in vietnam? *Health economics,* 25**,** 888-907.

Modena, F. & Gilbert, C. 2011. Shock responses of rural households in indonesia: A multinomial logit analysis.

Modigliani, F. & Brumberg, R. 1954. Utility analysis and the consumption function: An interpretation of cross-section data. *Franco Modigliani,* 1.

Modigliani, F. & Cao, S. L. 2004. The chinese saving puzzle and the life-cycle hypothesis. *Journal of Economic Literature,* 42**,** 145-170.

Mohanan, M. 2013. Causal effects of health shocks on consumption and debt: Quasi-experimental evidence from bus accident injuries. *Review of Economics and Statistics,* 95**,** 673-681.

Morgan, G. A., Harmon, R. J. & Maslin-Cole, C. A. 1990. Mastery motivation: Definition and measurement. *Early education and Development,* 1**,** 318-339.

Mossialos, E., Wenzl, M., Osborn, R. & Anderson, C. 2017. International profiles of health care systems. The commonwealth fund; 2016.

Münster, E., Rüger, H., Ochsmann, E., Letzel, S. & Toschke, A. M. 2009. Over-indebtedness as a marker of socioeconomic status and its association with obesity: A cross-sectional study. *BMC Public Health,* 9.

National Bureau of Statistics of China 2017. *China statistical yearbook 2017,* Beijing, China Statistics Press.

Nguyen, K. T., Khuat, O. T. H., Ma, S., Pham, D. C., Khuat, G. T. H. & Ruger, J. P. 2012. Coping with health care expenses among poor households: Evidence from a rural commune in vietnam. *Social science & medicine,* 74**,** 724-733.

Nguyet, N. T. N. & Mangyo, E. 2010. Vulnerability of households to health shocks: An indonesian study. *Bulletin of Indonesian Economic Studies,* 46**,** 213-235.

Oecd Statistics. 2016. *Household debt, total, % of te net disposable income* [Online]. Available: https://data.oecd.org/hha/household-debt.htm [Accessed 2018].

Ogden, C. L., Lamb, M. M., Carroll, M. D. & Flegal, K. M. 2010. Obesity and socioeconomic status in adults: United states, 2005-2008. *NCHS Data Brief*, 1-8.

Orlik, T. & Chen, F. 2015. Financing the next stage of china's development with consumer credit. *Paulson Policy Memorandum*.

Park, C.-Y. & Mercado, R. J. V. 2015. Financial inclusion, poverty, and income inequality in developing asia. *Asian Development Bank.*

Pickering, K., Monahan, M., Guariglia, A. & Roberts, T. E. 2017. Time to tighten the belts? Exploring the relationship between savings and obesity. *PloS one,* 12**,** e0179921.

Pohl, V., Neilson, C. & Parro, F. 2013. The effect of health shocks on employment: Evidence from accidents in chile.

Prentice, C., Mckillop, D. & French, D. 2017. How financial strain affects health: Evidence from the dutch national bank household survey. *Social Science and Medicine,* 178**,** 127-135.

Radloff, L. S. 1977. The ces-d scale:A self-report depression scale for research in the general population. *Applied Psychological Measurement,* 1**,** 385-401.

Rantanen, T., Volpato, S., Ferrucci, L., Heikkinen, E., Fried, L. P. & Guralnik, J. M. 2003. Handgrip strength and cause-specific and total mortality in older disabled women: Exploring the mechanism. *Journal of the American Geriatrics Society,* 51**,** 636-641.

Rashad, I. 2006. Structural estimation of caloric intake, exercise, smoking, and obesity. *The Quarterly Review of Economics and Finance,* 46**,** 268-283.

Richardson, T., Elliott, P. & Roberts, R. 2013. The relationship between personal unsecured debt and mental and physical health: A systematic review and meta-analysis. *Clinical Psychology Review,* 33**,** 1148-1162.

Riphahn, R. T. 1999. Income and employment effects of health shocks a test case for the german welfare state. *Journal of Population Economics,* 12**,** 363-389.

Roberts, H. C., Denison, H. J., Martin, H. J., Patel, H. P., Syddall, H., Cooper, C. & Sayer, A. A. 2011. A review of the measurement of grip strength in clinical and epidemiological studies: Towards a standardised approach. *Age and ageing***,** afr051.

Rohde, N., Tang, K. & Osberg, L. 2017. The self-reinforcing dynamics of economic insecurity and obesity. *Applied Economics,* 49**,** 1668-1678.

Rosenbaum, P. R. & Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 41-55.

Rowland, N. E. & Antelman, S. M. 1976. Stress-induced hyperphagia and obesity in rats: A possible model for understanding human obesity. *Science,* 191, 310-312.

Rubin, D. B. 2001. Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology,* 2, 169-188.

Rubin, D. B. & Thomas, N. 2000. Combining propensity score matching with additional adjustments for prognostic covariates. *Journal of the American Statistical Association,* 95, 573-585.

Ruhm, C. J. 2012. Understanding overeating and obesity. *Journal of Health economics,* 31, 781-796.

Saksena, P., Xu, K. & Durairaj, V. 2010. The drivers of catastrophic expenditure: Outpatient services, hospitalization or medicines. *World health report,* 21.

Salmasi, L. & Celidoni, M. 2017. Investigating the poverty-obesity paradox in europe. *Economics & Human Biology,* 26, 70-85.

Sarma, M. 2008. Index of financial inclusion. Indian Council for Research on International Economic Relations, New Delhi, India.

Schurer, S. 2014. Bouncing back from health shocks: Locus of control, labor supply, and mortality. *Browser Download This Paper*.

Selenko, E. & Batinic, B. 2011. Beyond debt. A moderator analysis of the relationship between perceived financial strain and mental health. *Social science & medicine,* 73, 1725-1732.

Siahpush, M., Huang, T. T. K., Sikora, A., Tibbits, M., Shaikh, R. A. & Singh, G. K. 2014. Prolonged financial stress predicts subsequent obesity: Results from a prospective study of an australian national sample. *Obesity,* 22, 616-621.

Smith, J. P., Strauss, J. & Zhao, Y. 2014. Healthy aging in china. *The journal of the economics of ageing,* 4, 37-43.

Smith, P. K., Bogin, B. & Bishai, D. 2005. Are time preference and body mass index associated?: Evidence from the national longitudinal survey of youth. *Economics & Human Biology,* 3, 259-270.

Sparrow, R., Van De Poel, E., Hadiwidjaja, G., Yumna, A., Warda, N. & Suryahadi, A. 2013. *Financial consequences of ill health and informal coping mechanisms in indonesia*, SMERU Research Institute.

St-Onge, M.-P. 2005. Relationship between body composition changes and changes in physical function and metabolic risk factors in aging. *Current Opinion in Clinical Nutrition & Metabolic Care,* 8**,** 523-528.

State Council of the People's Republic of China. 2015. *Development plan for promoting financial inclusion (2016-2020)* [Online]. Available: http://www.gov.cn/zhengce/content/2016-01/15/content_10602.htm [Accessed 2016].

State Council of the People's Republic of China. 2016. *Report on the work of the government* [Online]. Available: http://lianghui.people.com.cn/2016npc/n1/2016/0305/c402194-28174181.html [Accessed 2016].

Strauss, J. & Thomas, D. 1998. Health, nutrition, and economic development. *Journal of Economic Literature,* 36**,** 766-817.

Sui, Y. & Niu, G. 2018. The urban-rural gap of chinese household finance. *Emerging Markets Finance and Trade,* 54**,** 377-392.

Sundmacher, L. 2012. The effect of health shocks on smoking and obesity. *The European Journal of Health Economics,* 13**,** 451-460.

Sweet, E., Nandi, A., Adam, E. K. & Mcdade, T. W. 2013. The high price of debt: Household financial debt and its impact on mental and physical health. *Social Science & Medicine,* 91**,** 94-100.

The World Bank. 2013. *Universal financial access is vital to reducing poverty, innovation key to overcoming the enormous challenge, says president jim yong kim* [Online]. Available: http://www.worldbank.org/en/news/press-release/2013/10/11/universal-financial-access-vital-reducing-poverty-innovation-jim-yong-kim [Accessed 2014].

Torres, S. J. & Nowson, C. A. 2007. Relationship between stress, eating behavior, and obesity. *Nutrition,* 23**,** 887-894.

Trevisan, E. & Zantomio, F. 2016. The impact of acute health shocks on the labour supply of older workers: Evidence from sixteen european countries. *Labour Economics,* 43**,** 171-185.

Tsai, K. S. 2004a. *Back-alley banking: Private entrepreneurs in china*, Cornell University Press.

Tsai, K. S. 2004b. Imperfect substitutes: The local political economy of informal finance and microfinance in rural china and india. *World Development,* 32**,** 1487-1507.

Turvey, C. G. & Kong, R. 2010. Informal lending amongst friends and relatives: Can microcredit compete in rural china? *China Economic Review,* 21**,** 544-556.

United Nations 2002. World population ageing: 1950-2050. *Population Division, Department of Economic and Social Affairs [DESAJ, New York, United Nations*.

United Nations 2017. World population prospects: The 2017 revision, key findings and advance tables. *In:* DEPARTMENT OF ECONOMICS AND SOCIAL AFFAIRS, P. D. (ed.) *Working Paper No. ESA/P/WP/248.*

Van Doorslaer, E., Masseria, C., Koolman, X. & Group, O. H. E. R. 2006. Inequalities in access to medical care by income in developed countries. *Canadian medical association journal,* 174**,** 177-183.

Villar, J. G. & Quintana-Domeque, C. 2009. Income and body mass index in europe. *Economics & Human Biology,* 7**,** 73-83.

Von Hippel, P. T. & Lynch, J. L. 2014. Why are educated adults slim—causation or selection? *Social Science & Medicine,* 105**,** 131-139.

Wagstaff, A. 2007. The economic consequences of health shocks: Evidence from vietnam. *Journal of health economics,* 26**,** 82-100.

Wagstaff, A. & Doorslaer, E. V. 2003. Catastrophe and impoverishment in paying for health care: With applications to vietnam 1993–1998. *Health economics,* 12**,** 921-933.

Wagstaff, A. & Lindelow, M. 2010. Are health shocks different? Evidence from a multi-shock survey in laos.

Wang, H., Zhang, L. & Hsiao, W. 2006. Ill health and its potential influence on household consumptions in rural china. *Health Policy,* 78**,** 167-177.

Wang, L., Wang, A., Zhou, D., Fitzgerald, G., Ye, D. & Jiang, Q. 2016. An empirical analysis of rural-urban differences in out-of-pocket health expenditures in a low-income society of china. *PloS one,* 11**,** e0154563.

Wang, X. & Wen, Y. 2012. Housing prices and the high chinese saving rate puzzle. *China Economic Review,* 23**,** 265-283.

Wang, Z., Li, X., Chen, M. & Si, L. 2018. Social health insurance, healthcare utilization, and costs in middle-aged and elderly community-dwelling adults in china. *International Journal for Equity in Health,* 17**,** 17.

Webbink, D., Martin, N. G. & Visscher, P. M. 2010. Does education reduce the probability of being overweight? *Journal of Health Economics,* 29**,** 29-38.

Webley, P. & Nyhus, E. K. 2001. Life-cycle and dispositional routes into problem debt. *British journal of psychology,* 92**,** 423-446.

Wei, S.-J. & Zhang, X. 2011. The competitive saving motive: Evidence from rising sex ratios and savings rates in china. *Journal of Political Economy,* 119**,** 511-564.

Willett, W. C. 1997. Weight loss in the elderly: Cause or effect of poor health? : Oxford University Press.

Wooldridge, J. M. 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of applied econometrics,* 20**,** 39-54.

Wooldridge, J. M. 2010. *Econometric analysis of cross section and panel data*, MIT press.

World Health Organization 2015. People's republic of china health system review. Manila: WHO Regional Office for the Western Pacific.

World Health Organization. 2018. *Ageing and health* [Online]. Available: http://www.who.int/news-room/fact-sheets/detail/ageing-and-health [Accessed June 2018].

Yilmazer, T. & Scharff, R. L. 2014. Precautionary savings against health risks: Evidence from the health and retirement study. *Research on aging,* 36**,** 180-206.

You, X. & Kobayashi, Y. 2011. Determinants of out-of-pocket health expenditure in china. *Applied health economics and health policy,* 9**,** 39-49.

Zeldes, S. P. 1989. Consumption and liquidity constraints: An empirical investigation. *Journal of Political Economy,* 97**,** 305-346.

Zhang, A., Nikoloski, Z. & Mossialos, E. 2017. Does health insurance reduce out-of-pocket expenditure? Heterogeneity among china's middle-aged and elderly. *Social Science & Medicine,* 190**,** 11-19.

Zhang, G. 2008. The choice of formal or informal finance: Evidence from chengdu,china. *China Economic Review,* 19**,** 659-678.

Zhang, J., Wang, L. & Wang, S. 2012. Financial development and economic growth: Recent evidence from china. *Journal of Comparative Economics,* 40**,** 393-412.

Zhang, L. & Rashad, I. 2008. Obesity and time preference: The health consequences of discounting the future. *Journal of Biosocial Science,* 40**,** 97-113.

Zhang, Y. & Wan, G. 2004. Liquidity constraint, uncertainty and household consumption in china. *Applied Economics,* 36**,** 2221-2229.

Zhu, X., Whalley, J. & Zhao, X. 2014. Intergenerational transfer, human capital and long-term growth in china under the one child policy. *Economic Modelling,* 40**,** 275-283.

Zucchelli, E., Jones, A. M., Rice, N. & Harris, A. 2010. The effects of health shocks on labour market exits: Evidence from the hilda survey. *Australian Journal of Labour Economics,* 13**,** 191.