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Stuttgart, February 8th, 2015 Peng Nie

Contents

List of Abbreviations

Adolescent Health	Add Health
Body Mass Index	BMI
Blow-Up and Cluster	BUC
China Health and Nutrition Survey	CHNS
Chinese Center for Disease Control and Prevention	CCDC
Center for Disease Control	CDC
China Urban Household Income and Expenditure Surveys	CUHIES
Chinese Household Income Project Survey	CHIP
Confidential Intervals	CI
Coronary Heart Disease	CHD
Diabetes Mellitus	DM
Diastolic Blood Pressure	DBP
Differences-In-Differences	DID
Eating and Activity in Teens	EAT
Exponential Random Graph Model	ERGM
Food and Agriculture Organization	FAO
Food Security	FS
Fixed Effects	FE
Gross Domestic Products	GDP
Grandmother Childcare Hours	GCH
General Method of Moments Model	GMM
German Socioeconomic Panel	GSOEP
Grade Point Average	GPA
Health Status	HS

Hamilton Depression Scale	HDS
International Fund for Agricultural Development	IFAD
International Obesity Task Force	IOTF
Instrumental Variable	IV
Log-Log Squared Model	LLS
Log-Log Inverse Model	LLI
Locally Weighted Scatterplot Smoothing	LOWESS
Longitudinal Logistic-Regression Model	LLM
Limited Information Maximum Likelihood Model	LIML
Maternal Working Hours	MWH
Monte Carlo Simulations	MCS
Mean Regression	MR
Natural Experiment	NE
Number of Cigarettes Smoked	NCS
Organization for Economic Cooperation and Development	OECD
Ordinary Least Squares	OLS
Panel Data	PD
Partially Linear Model	PLM
Physical Activity Module	PAM
Profile of Mood State	POMS
Quantile Regression Model	QR
Recommended Dietary Intakes	RDIs
Random Effects	RE
Semiparametric Instrumental Variable Estimate	SIV
School Health Action, Planning, and Evaluation System	SHAPES
Stochastic Actor-Oriented Models	SAOMs
Systolic Blood Pressure	SBP
Self-Reported Health	SRH
Two Stage Least Squared Model	TSLS

Working Group on Obesity in China	WGOC
World Food Program	WFP
World Health Organization	WHO
Weekly Work Hours	WH
Waist Circumference	WC

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Chapter 1 Introduction

1.1 General introduction

Since the Reform and Opening Policy in 1978, China has experienced remarkably economic growth, with per capita Gross Domestic Products (GDP) increasing from 381 yuan in 1978 to 38420 yuan in 2012 (National Bureau of Statistics of China, 2013). The process of urbanization, especially the proportion of urban residence, has also speeded up during the same period, rising from 17.9% to 52.6% (National Bureau of Statistics of China, 2013). However, such a rapid economic and social transformation has resulted in not only income increase but nutrition and dietary transition (featured as high dietary fat, animal-source foods and edible oils) with a markedly accelerating pace (Zhai et al., 2009). In contrast, over such an impressive economic growth, the reputation for health in China has been shrinking (Tang et al., 2008). The diet-related non-communicable diseases, in particular, obesity, diabetes, hypertension and heart disease, have recently been prevalent (Sun et al., 2011). Specifically, for example, the prevalence of adult overweight has tripled, increased from 11.7% in 1991 to 29.2% in 2009 (Gordon-Larsen et al., 2014). More importantly, Liang et al. (2012) have also confirmed the secular upward trend in general and abdominal adiposity among Chinese children and adolescents aged 6-17 years. Those sharp increases in adiposity among younger Chinese cohorts are particularly worrying. However, it is worth noting that, those abovementioned non-communicable diseases are the major causes of morbidity, disability and mortality in China (He et al., 2005): it is estimated that 80% of deaths and 70% of disability-adjusted life-year lost are attributable to chronic and non-communicable diseases in China (Wang et al., 2005).

It is no doubt that those adverse changes in health, nutrition and diet, interplayed by rapid economic and social transitions, pose a great challenge for the health care system in China and also potential chronic disease-related economic burdens (Tang et al., 2008; Zhao et al., 2008). As emphasized by Tang et al. (2008), social drivers of health have become more inequitable on many fronts, which would put a further drain for these challenges in nutrition and dietary transformations. Therefore, in light of the decline of health status and the increased inequality of socio-economic determinants in China, it is vitally important to reexamine health and nutrition situations in Chinese population from different perspectives of socio-economic determinants.

Thus, the major objective of this dissertation is to enhance the understanding of the impacts of some socio-economic factors (see, e.g. income, maternal employment, social networks and work hours) on a rich set of specific aspects of health (including objective and subjective measures) and nutrition in China by using the data from the China Health and Nutrition Survey (CHNS) spanning from 1991 to 2009. Note that this dissertation is a combination of four studies and general backgrounds of each study are as follows:

As have mentioned previously, with the rapid economic growth and urbanization process, the prevalence of overweight and obesity among Chinese children and adolescents has increased alarmingly (see, e.g., Liang et al., 2012). Given that employed mothers might spare less time at home and give rise to the increased probability of unhealthy dietary and sedentary patterns among children, the increase in maternal employment has been regarded as one of important drivers for childhood obesity. However, it is worth noting that related studies are strongly dominated by the Western world (see Anderson, 2003; Cawley and Liu, 2012) and it is hard to generalize it. Considering higher female employment participation and also common pattern of informal childcare like grandparenting in Chinese context, therefore, it is tempting to examine the relation between maternal employment and childhood obesity within a non-Western domain. Consequently, the first study within Chapter 2 will investigate how maternal employment is associated with childhood adiposity in China.

Meanwhile, as emphasized by Zhai et al. (2009), China is suffering from double burdens associated with undernutrition and overnutrition. Although income levels in China have increased greatly, *the State of Food Insecurity in the World 2012* reports that 158 million Chinese are still in hunger (FAO, WFP and IFAD, 2012). Furthermore, 122 million Chinese were still in poverty (National Bureau of Statistics of China, 2012). Hence, income changes could affect household food security, in particular, calorie intakes, thereby taking a close look at calorie-income elasticities are crucial and implicative of the effectiveness of income-mediated policies for food security. Even though a wealth of literature has touched on this topic, magnitudes of calorie-income elasticities vary greatly, even for China. Therefore, the second study within Chapter 3 takes a comprehensive look at calorie-income elasticities in China.

As have stated before, the issue of general and abdominal obesity among Chinese children and adolescents are worrisome. Yet despite that childhood and adolescent adiposity is attributable to the imbalance between calorie intakes and physical activity, the causes of social behaviors (more specifically, like peer effects) associated with individual obesity is still not clear-cut, especially mechanisms through which social networks like peers work on individual bodyweight. Mora and Gil (2013) argue that peer effects might be affected by socio-cultural patterns and individuals within collective societies are more liable to be influenced by peers compared with those within individualistic societies. In contrast to American children in individualistic environments, Chinese children are more vulnerable to other's opinions and judgments (Fung, 1999). As a consequence, the differences in peer effects on individual bodyweight may be observable in the U.S. and China. Moreover, it is particularly important to highlight that current existing studies mainly focus on adolescents and adults. Nevertheless, understanding peer effects on childhood adiposity is of great significance primarily because, as emphasized by Dishion and Tipsord (2011), children's consumption behaviors are influenced by their peers. More importantly, childhood adiposity could result in persistent adulthood overweight or obesity (Loh and Li, 2013). Just based on this background, the third study within Chapter 4 thus assess whether obesity in both children and adolescents is associated with peer effects in China. It also takes a closer examination of the pathways through which peer effects might operate.

Recently, some argue that the remarkable economic miracle in China might have happened at the high expense of long work hours of Chinese employees (Smyth et al., 2013). Meanwhile, the concern of the Chinese phenomenon of "*Guolaosi*" (meaning death stemmed from long work hours) has stepped into the spotlight. In addition, although a broad body of literature has examined the impacts of long work hours on health outcomes, inconsistencies in the results remain exist, which depend critically on not only various definitions of long work hours and health outcomes, but individual heterogeneity and different adoptions for potential covariates (Bannai and Tamakoshi, 2014). Furthermore, to the best of our knowledge, the only three studies in China (Frijters et al., 2009; Verité, 2004; Zhao, 2008) all investigate subjective measures of health via cross-sectional data. Therefore, the fourth study within Chapter 5 aims to assess the effects of long work hours on both subjective and objective health among Chinese employees using cross-sectional and panel data.

1.2 The outline of the thesis

The outline of this dissertation is structured as follows:

Chapter 2 analyzes the relation between maternal employment and childhood obesity in China, which provides a non-Western comparison in this field. More importantly, it further explores how maternal employment is related to the two major drivers of obesity: diet and physical activities, which is mostly ignored by most existing studies. Considering the importance of time investment in maternal employment and grandparenting in China, it also checks the relationship in the nonlinearity of mother working hours, grandmother childcare hours and childhood adiposity.

Chapter 3 then details the impact of income upon individual calorie intake. It goes beyond an examination of the relation between income and calorie intakes using parametric approaches. Rather, employing a variety of parametric, nonparametric and semiparametric techniques, based on the cross-sectional and panel data from the CHNS, allows for addressing some methodological challenges. It takes a comprehensive look at calorie-income elasticities in China, which might be implicative of some income-mediated policies for food security in China and even some developing countries.

Chapter 4 assesses the nexus between peer effects (one of the most important aspects of social networks) and childhood and adolescent obesity. It expands the empirical work beyond the Western domain in light of different cultural backgrounds between individualistic and collective societies. Further, it broadens the dominant front of adolescents and adults by analyzing children as well. The use of self-perceived perceptions of body weight allows for an exploration of the relation between peer effects and individual perceptions of weight status. It provides insights into understanding pathways by which peer effects operate within a relatively broader environment.

In Chapter 5, particular emphasis is given to the impact of long work hours on health. It provides a comprehensive picture of how long work hours are related to health, not only subjective but objective measures. Also, it provides a valuable comparison with existing studies predominantly in the Western world. More importantly, it explores several potential mechanisms through which long work hours could impact upon health. In particular, it investigates the relation between long work hours and specific lifestyles, such as sleep, diet (calorie and fat intakes, time spent food preparation and cooking), physical activities. Apart from cross-sectional settings, it also adopts a panel analysis, which allows for controlling for unobserved individual heterogeneity.

Finally, Chapter 6 gives a summary of preceding chapters and draws some conclusions.

Chapter 2 Maternal Employment and Childhood Obesity in China: Evidence from the China Health and Nutrition Survey[1]

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Abstract

Using five waves from the China Health and Nutrition Survey (CHNS), we investigate the association between maternal employment and obesity in children aged 3–17 in both rural and urban China. Using BMI and waist circumference as measures for pediatric adiposity, we provide scant evidence for its relation to maternal employment. We also find no strong association between maternal employment and our measures for children's diet and physical activity. Our study also suggests that grandparenting could have beneficial effects on childhood obesity.

Keywords: Maternal employment; childhood obesity; China

JEL Classification Codes: I12, J13, J22

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2.1 Introduction

The alarming rise in obesity rates among children and adolescents is affecting countries around the globe (Cawley, 2009; Sassi, 2010; Wang and Lobstein, 2006), with China being no exception. In fact, like economic growth and urbanization, the prevalence of overweight and obesity among Chinese children and adolescents is rapidly on the increase (Cui et al., 2010; Liang et al., 2012; Song et al., 2013; Yu et al., 2012; Zhang et al., 2012; Zhang and Wang, 2012). For example, the latest survey by the Chinese Center for Disease Control and Prevention's (CCDC) reports that in 2011, the number of overweight and obese children below the age of 18 years was 120 million (Li, 2012). Based on the International Obesity Task Force (IOTF) reference, the prevalence of general obesity and abdominal obesity in Chinese children aged 6-17 has increased dramatically from 1993 to 2009: general obesity increased from 6.1% to 13.1% and abdominal obesity from 4.9% to 11.7% (Liang et al., 2012). These levels of childhood obesity are expected to increase the prevalence of chronic diseases such as cardiovascular disease, strokes, type 2 diabetes, and a subset of cancers (Hill and Peters, 1998; Hill et al., 2003; Hossain et al., 2007), as well as certain social and mental health problems (OECD, 2012). In China, it is estimated that approximately 1.7 million 7–18 year old children already have diabetes and 27.7 million are prediabetic (Yan et al., 2012).

One reason proposed for the increase – and one that has received much academic and popular attention – is the rise in maternal employment, whose relation to childhood obesity is the subject of a large body of literature (see, e.g.,Anderson, 2003; Benson and Mokhtari, 2011; Cawley and Liu, 2012; Fertig et al., 2009; Herbst and Tekin, 2011). The rationale underlying this conjecture is that employed mothers spend less time at home, which could result in an increase in children's unhealthy eating behaviors and sedentary activities. Nevertheless, virtually all studies testing this assumption are based on Western data, particularly U.S. data, which provide robust empirical evidence that maternal employment actually has a positive effect on childhood obesity (see, e.g., Anderson, 2003). The evidence for several European countries, however, is nowhere near as clear-cut (see Greve, 2011; Gwozdz et al., 2013).

In this paper, we contribute to the research stream by analyzing the relation between maternal employment, childhood obesity, diet, and physical activity in China, a particularly interesting topic for three reasons: First, research outside the Western world is so limited that it is impossible to assess the extent to which the positive relation between maternal employment and childhood obesity can be generalized; especially, in light of the recent ambiguous evidence for Europe. Second, Chinese female employment rates are among the highest in Asia (Crabtree and Pugliese, 2012),[2] with a 72 percent employment rate among mothers aged 25–34 who have children under the age of 6 (Third Survey on Chinese Women's Social Status, cited in Wang, 2011). If maternal employment *per se* affects child obesity, then arguably, this influence should be observable in China. Third, child care in China is to a large degree carried out by grandparents, which lessens the mother's dual burden of household chores and employment (Cooke, 2005). Yet the fact that nearly a quarter of the nation's children and almost a third of its rural children are growing up with grand- and great

[2] More details are available at http://www.gallup.com/poll/158501/china-outpaces-india-women-workforce.aspx.

grandparents has received substantial negative press (e.g., Luo, 2005; Stack, 2010) on the grounds that this "left behind" generation faces stark psychological and emotional challenges that could translate into obesity.

The purpose of this study, therefore, is to improve our understanding of the association between pediatric adiposity and female employment by using data from the China Health and Nutrition Survey (CHNS). To the best of our knowledge, this analysis is the first attempt to evaluate the association between maternal employment and childhood obesity using Chinese data.[3] The choice of the CHNS dataset is particularly appropriate because the survey includes both useful anthropometric measures of obesity and rich information on children's diets and physical activity enables direct analysis of these two main drivers of obesity. Based on our results, we conclude overall that maternal employment is not significantly related to obesity, diet, and physical activity in Chinese children aged 3–17 years.

The remainder of the paper is structured as follows: Section 2.2 reviews the relevant literature, Section 2.3 describes the data and methods, Section 2.4 presents the results, Section 2.5 reports some robustness tests and Section 2.6 summarizes the conclusions.

2.2 Prior research

Most of the growing body of literature on the maternal employment-child obesity relation originates in the United States (Anderson, 2003; Benson and Mokhtari, 2011; Cawley and Liu, 2012; Fertig et al., 2009; Herbst and Tekin, 2011; Liu et

[3] Liu et al. (2013) investigate changes of China's urban-rural child (below 18 years old) health and nutritional status over 1989-2006 and find that there is no association of maternal employment status with z scores of child height-for-age and weight-for-age, and also anthropometric outcomes of being stunted and being underweight.

al., 2009; Miller, 2011; Miller and Han, 2008; Morrissey et al., 2011; Ruhm, 2008). Nevertheless, research on this topic has also been conducted in Australia (Bishop, 2011; Brown et al., 2010; Champion et al., 2012; Zhu, 2007), Canada (Baker and Milligan, 2008; Chia, 2008; Phipps et al., 2006), Japan (Gaina et al., 2009), the UK (Champion et al., 2012; Hawkins et al., 2008; Scholder, 2008), Denmark (Greve, 2011), Spain (Garcia et al., 2006), and in eight other European countries (Gwozdz et al., 2013).[4] For the purposes of this study, two insights from this research stream are particularly important.

First, studies for the U.S. provide strong evidence of a positive effect of maternal employment on childhood obesity, although the magnitude of this effect varies substantially. Although this positive effect tends to be supported by studies for the UK (Champion et al., 2012; Hawkins et al., 2008; Scholder, 2008), European studies are far less conclusive, giving evidence of no effects (Gwozdz et al., 2013) or even negative effects (Greve, 2011). The only non-Western study that we are aware of is Gaina et al.'s (2009) investigation of the relation between maternal employment status and nutritional patterns in 12 to 13 year-old Japanese children, which finds a positive effect of the former on the latter.

Second, very few studies look directly at how maternal employment could affect the two main transmitters of obesity: diet and physical activity. As regards the first, a few studies do examine how maternal employment affects meal patterns (Gaina et al., 2009; Neumark-Sztainer et al., 2003; Siega-Riz et al., 1998), expenditures on purchased meals (Horton and Campbell, 1991; McCracken and Brandt, 1987), and time spent cooking (Cawley and Liu, 2012). Only Gwozdz et

[4] See Greve (2008), Gwozdz et al. (2013), and Scholder (2008) for useful literature reviews of these extant studies.

al. (2013), however, analyze how maternal employment affects caloric intake, and they identify no significant differences between the intake of 2–9 year old children of employed and nonemployed mothers in 8 European countries. In terms of physical activity, although a number of studies document an association between maternal employment and an increase in children's sedentary activities such as watching TV (e.g., Fertig et al., 2009; Ziol-Guest et al., 2012), other studies observe no such relation (Bonke and Greve, 2012; Gwozdz et al., 2013). Moreover, we are unaware of any studies that analyze the effect of maternal employment on children's diet and physical activity in China.

2.3 Data and methods

2.3.1 Study design and population

The data used in the present study are taken from the China Health and Nutrition Survey (CHNS), which has been conducted in 8 waves since 1989 (1989, 1991, 1993, 1997, 2000, 2004, 2006 and 2009). The survey sample was drawn from 9 provinces (Liaoning, Heilongjiang[5], Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou) with different social, economic, and health situations. The multistage random cluster sampling method (Popkin et al., 2010), which is based on income level (high, mediate, and low) and weighted sampling, consists of the following steps. After randomly selecting four counties and two cities within each province, the CHNS team identifies villages and towns in each county, and urban and suburban regions in each city. From each of these communities, 20 households are selected (Popkin et al., 2010).[6]

[5] Heilongjiang province was introduced as the ninth province in1997.

[6] See Liu (2008) and Popkin et al. (2011) for more detailed information about the CHNS.

In this present study, the selected sample comprises 2618 children aged 3 to 17 years, with 155, 318, 643, 661, and 841, respectively, from the 1997, 2000, 2004, 2006, and 2009 survey waves. Because our targeted indicators are selected from different survey items for which some information may be missing, we perform our analyses on different sample sizes. In particular, we analyze three age groups separately: 3–17 year olds, 3–5 year olds, and 6–17 year olds, the last chosen to reflect the fact that Chinese children generally enroll in primary education at age 6. The estimates for the effect of maternal employment on child diet are for children aged 3–17 years based on data from 1997, 2000, 2004, 2006, and 2009. However, because of data availability constraints, the estimates for the effect of maternal employment on child physical activity are restricted to children aged 5–17 years in the data from 2004, 2006, and 2009. [7]

2.3.2 Study variables

Anthropometric measures

We use two measures for obesity: body mass index (BMI) for general obesity and waist circumference for central obesity. The first is calculated as weight in kilograms divided by squared height in meters, with weight measured with lightweight clothing on a calibrated beam scale and expressed in kilograms to the nearest 0.1 kg. Height is measured without shoes on a portable stadiometer and expressed in centimeters to the nearest 0.1 cm (Xi et al., 2012). Although several growth references are available, including those from the Center for Disease Control (CDC) 2000, WHO 2006 and 2007, and the International Obesity Task

[7] In the CHNS, information about physical activities of children (especially time spent on these activities), is available from 2004 onwards. With regards to time devoted to physical activities for children aged below 5 years, the data are mostly unavailable due primarily to large missing values.

Force (IOTF) (developed by Cole et al., 2000), the IOTF growth charts, based not only on the U.S., Great Britain, Netherlands, and Brazil but also on Hong Kong and Singapore, are probably the most appropriate for evaluating Chinese overweight and obesity (see also Ma et al., 2011; Monasta et al., 2010). We therefore use the BMI *z*-scores from the IOTF growth charts.

BMI, however, although the most common measure of adiposity in studies on maternal employment and childhood obesity, is so general a measure that it may be incapable of accurately reflecting obesity changes, especially as it gives no indication of fat distribution (Dermerath et al., 2006; McCracken and Brandt, 1987; Rolland-Cachera, 2011). We therefore also use waist circumference[8] measured horizontally with an inelastic tape at the midpoint between the lowest rib and the iliac crest (Liang et al., 2012), and expressed in centimeters to the nearest 0.1 cm. Weight, height, and waist circumference were all measured by trained health workers based on WHO's (1995) standard protocol. The *z*-scores for waist circumference are derived from the British 1990 growth reference (see Cole et al., 1998).

Maternal employment

Our independent variables are selected based on a traditional production function in which child health outcomes rely on parental nonmarket time and other investments (Ruhm, 2004, 2008). We use a dummy variable to capture maternal employment status, measured by the question "Are you presently working?" If a woman is currently employed, the employment variable equals 1 and 0 otherwise, so nonemployed women are the reference group.

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[8] It is worth noting that among 6–17 year old Chinese, the increase in waist circumference is much larger than that in BMI (Liang et al., 2012).

As a robustness check, we also employ maternal working hours (MWH), measured by “how many hours did you work during the past week?” In order to capture potential nonlinearities in maternal working hours we implement dummy variables. Specifically, maternal working hours are divided into 7 groups: 0 (as the reference group), $0<\text{MWH}<20$, $20\leq\text{MWH}<30$, $30\leq\text{MWH}<40$, $40\leq\text{MWH}<50$, $50\leq\text{MWH}<60$ and $\text{MWH}\geq60$.

We also include three sets of control variables: child, family, and socioeconomic characteristics. Our specification is thus similar to that of Gwozdz et al. (2013).

Child characteristics

The set of child characteristics includes four variables: age, gender, birth order, and numbers of siblings, two of which, gender and birth order, are dummy variables. The gender dummy equals 1 if the child is a boy, 0 otherwise, and the birth order dummy equals 1 if the child’s birth order is first, 0 otherwise.

Family characteristics

With regard to family characteristics, we include six variables: parental age (mother/father), parental BMI (mother/father), household size, and father’s employment status, which is a dummy equal to 1 if the father is presently employed, 0 otherwise.

Socioeconomic characteristics

A third set of control variables measures the socioeconomic characteristics of household net income and parental education level. The latter is represented by years of schooling. Household income data were collected by trained interviewers based on a household questionnaire.

Our econometric model is as follows:

$$W = \beta_0 + M\beta_1 + C\beta_2 + F\beta_3 + S\beta_4 + T\beta_5 + P\beta_6 + \mu \qquad (1)$$

where W is a matrix of child obesity measures, M is a matrix of mother employment status, C is a matrix of child variables, F is a matrix of family variables, and S is a matrix of socioeconomic variables. T is a matrix of survey year dummies with 1997 as the reference year, P is a matrix of provincial dummies (Liaoning province as the reference), μ is a matrix of disturbance error terms, and β_1 is the key coefficient of interest. For equation (1), we estimate both OLS and quantile regressions.

It is important to stress, however, that establishing a causal relation between maternal employment and child weight is impossible in our cross-sectional setting, especially given that maternal employment status might be endogenous. In this case, determining the magnitude and direction of a possible bias a priori is not only difficult but purely speculative. In our analysis, therefore, we try to account for endogeneity by using a very rich set of child and family characteristics.[9]

Nonetheless, it is still impossible to test whether or not our variable set eliminates all unobserved heterogeneity. It is worth noting, however, that all the IV-based research of which we are aware (e.g., Greve, 2011) shows maternal employment status to be clearly exogenous, which may lend some support for the

[9] We also conducted our analysis with the use of the two-stage estimation procedure proposed by Lewbel (2012). In our case, we adopt child birth order and year dummies as instrumental candidates and our results show that there is no association between maternal employment and child adiposity. The estimate results of Lewbel's technique are not reported here, but available from the authors upon request.

assumption that the endogeneity of maternal employment may not be a major problem in such models.

Diet

Because obesity is generally a consequence of excess caloric intake combined with insufficient physical activity, this study measures children's dietary patterns using two variables: meals at home and caloric intake (kcal). The first is calculated as the ratio of meals taken at home (over 3 days) to total meal times; the second as the average daily caloric intake (averaged over 3 days). With the exception of children under the age of 12 (whose individual dietary intake is reported by the mother or caregiver), all respondents were asked directly about all food consumed inside and outside the home. Also recorded were food items, meal types, and places of food consumption on the previous day (Cui and Dibley, 2012).

Physical activity

A child's physical activity is measured by calculating the time a child spends weekly on physical exercise before or after school (measured in minutes per week). This physical exercise consists of 4 major types: gymnastics, track and swimming, ball games (e.g., basketball, volleyball, soccer, table tennis), and other sports (e.g., martial arts) (Dearth-Wesley et al., 2012). We also compute sedentary activity based on the total time spent watching TV, doing homework, and reading and writing (measured in minutes per week).

Our econometric model is thus

$$P = \theta_0 + M\theta_1 + C\theta_2 + F\theta_3 + S\theta_4 + T\theta_5 + P\theta_6 + \mu \qquad (2)$$

where P is a matrix of diet and physical activity of children, M is a matrix of mother's employment status, C is a matrix of child variables, and F is a matrix of family characteristics. S is a matrix of socioeconomic variables. T is a matrix of survey year dummies with 1997 as the reference year, P is a matrix of provincial dummies (Liaoning province as the reference), μ is a matrix of disturbance error terms, and θ_1 is the key coefficient of interest. For equation (2), we estimate OLS regressions.

2.3.3 Statistical Analysis

Our econometric models examine the association between childhood obesity and maternal employment using Ordinary Least Squares (OLS) regressions, which reveal substantial differences between urban and rural areas in China, especially with regards to economic development. Hence, as a robustness test, we also undertake an urban-rural comparison using quantile regressions to investigate the different impacts of maternal employment on pediatric adiposity at different points along the obesity measure distribution (see, e.g., Herbst and Tekin, 2011). We report the descriptive statistics in Appendix Table A2.1. The prevalence of employed mothers in our analysis is 78.8% in comparison to 21.2% unemployed mothers. Additionally, in urban area, the prevalence of employed mothers is 71.8%, which is approximately 10% lower than that of rural area[10] (not reported in Table A2.1).

[10] In our dataset, 533 mothers are currently employed but 209 mothers are unemployed in urban area, while in rural area, the number of employed and unemployed mothers are 1531 and 345, respectively.

2.4 Results

2.4.1 Maternal employment and childhood obesity

The regressions[11] examining the association between maternal employment and child obesity among the different age groups (see Table 2.1) indicate no significant relation between these two variables, a finding contrary to those in most previous studies but in line with Gwozdz et al. (2013) and Greve (2011). It is also worth noting that nearly all coefficients for maternal employment are negative, albeit not significantly so. This insignificant association of maternal employment with childhood obesity is further highlighted by evidence from the urban-rural comparison (see Table 2.1).

Table 2.1 OLS estimates of maternal employment on obesity measures

Variables	BMI *z*-score			Waist circumference *z*-score		
Ages	3–17	6–17	3–5	3–17	6–17	3–5
All	-0.087	-0.056	-0.145	-0.039	-0.092	0.317
	(0.065)	(0.067)	(0.163)	(0.101)	(0.105)	(0.309)
Observations	2614	1863	751	2163	1740	423
Adj. R^2	0.090	0.135	0.023	0.045	0.049	0.015
Urban	-0.086	-0.008	-0.319	0.021	0.059	-0.166
	(0.115)	(0.120)	(0.322)	(0.155)	(0.162)	(0.455)
Observations	738	537	201	603	490	113
Adj. R^2	0.104	0.153	0.019	0.040	0.053	0.000
Rural	-0.078	-0.082	-0.069	-0.074	-0.178	0.594
	(0.079)	(0.084)	(0.186)	(0.130)	(0.138)	(0.400)
Observations	1876	1326	550	1560	1250	310
Adj. R^2	0.087	0.125	0.033	0.049	0.057	0.039

Source: China Health and Nutrition Survey, authors' calculations.
Note: Dependent variables are BMI z-score and waist circumference z-score. Controls include child, family and socioeconomic characteristics, dummies of year (1997 as the reference year), province (Liaoning as the reference) and urban (rural as the reference). Urban-rural split analysis is without urban dummy. 3-17 means 3≤child age≤17, 6-17 means 6≤child age≤17, and 3-5 means 3≤child age<6. Robust standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

[11] Results also indicate that parental education is positively associated with child adiposity, which is echoed by some previous studies (Johnson et al., 2006; Lakshman et al., 2013).

In the results for the quantile regressions, maternal employment is only significantly *negatively* linked to BMI at the 50% and 95% cut-offs: that is, at the upper end of the BMI distribution (see Table 2.2). Taken at face value, this result seems to support the negative influence of maternal employment on BMI indicated in Greve (2011). Interestingly, however, using waist circumference as another variable for adiposity produces no significant results, which echoes Burkhauser and Cawley's (2008) conclusion that different measures of fatness can give rise to quite different results.

Table 2.2 Quantile regression of maternal employment on obesity measures for 3-17 children

Variables	(10%)	(25%)	(50%)	(75%)	(85%)	(95%)
BMI *z*-score	-0.010	-0.098	-0.142**	-0.109	-0.098	-0.269*
	(0.106)	(0.082)	(0.063)	(0.087)	(0.088)	(0.151)
Observations	2614	2614	2614	2614	2614	2614
Pseudo R^2	0.053	0.046	0.065	0.083	0.090	0.086
Waist circumference *z*-score	0.060	0.032	-0.100	-0.124	-0.079	0.022
	(0.200)	(0.118)	(0.088)	(0.084)	(0.116)	(0.127)
Observations	2163	2163	2163	2163	2163	2163
Pseudo R^2	0.051	0.034	0.034	0.036	0.051	0.071

Source: China Health and Nutrition Survey, authors' calculations.
Note: Dependent variables are BMI z-score and waist circumference z-score. Controls include child, family and socioeconomic characteristics, dummies of year (1997 as the reference year), province (Liaoning as the reference) and urban (rural as the reference). Bootstrapped standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Overall, our analysis provides little evidence that children's current obesity is positively associated with current maternal employment status. However, as we cannot rule out the possibility that current maternal employment affects future obesity levels, we also analyze the effect of maternal employment on the direct drivers of obesity. If this effect is present, current maternal employment should have an immediate (i.e., not lagged) effect on children's diets and physical activity. [12]

2.4.2 Maternal employment, diet, and physical activity

As is evident from the estimates in Table 2.3, maternal working status is not significantly associated with caloric intake, meals at home, physical exercises, and/or sedentary activities. Nor does the urban-rural comparison reveal significant results other than for meals at home in urban areas, which is significant at the 5% level.

Table 2.3 OLS estimates of maternal employment on diet and physical activity

Variables	Diet (ages 3–17)		Physical activity (ages 5–17)	
	Calorie	Meals	PE	SA
All	-0.015	0.035	0.079	-0.018
	(0.018)	(0.040)	(0.080)	(0.034)
Observations	2614	1768	563	941
Adj. R^2	0.273	0.159	0.008	0.048
Urban	-0.021	0.188^{**}	0.099	-0.019
	(0.033)	(0.083)	(0.112)	(0.055)
Observations	738	494	217	321
Adj. R^2	0.197	0.200	0.046	0.107
Rural	-0.027	0.008	0.038	-0.025
	(0.021)	(0.040)	(0.120)	(0.044)
Observations	1876	1274	346	620
Adj. R^2	0.303	0.088	0.000	0.071

Source: China Health and Nutrition Survey, authors' calculations.
Note: The sample size of diet estimates is restricted to 1997, 2000, 2004, 2006 and 2009 (dependent variables are translog calorie intake and meals at home). And the sample size for estimates of physical activity and sedentary activities is restricted to 2004, 2006 and 2009 (dependent variables are translog physical exercise and sedentary activity). Controls include child, family and socioeconomic characteristics, dummies of year (1997 as the reference year), province (Liaoning as the reference) and urban (rural as the reference). Urban-rural split analysis is without urban dummy. PE means physical exercise. SA means sedentary activities. Robust standard errors are in parentheses, $^{*}p<0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

[12] If child weight is assumed to be a short-term outcome, child height might be a better proxy for long-term effects. Maternal employment may have a large impact on child height through increasing household income and improving child nutritional status. However, in our case, the correlation between maternal employment (including employment participation or working hours) and child height is negligibly small but negative.

2.5 Robustness checks

2.5.1 Do maternal working hours really matter?

Our analysis above focused on maternal working status as the CHNS has a large share of missing values with regards to the working time of the mother (more than 50% of observations in our sample of mothers). Nevertheless, as the length of the working day may be more informative than the employment status (see also Scholder, 2008), we analyze the working time information for a sample for which information is available. In order to explore nonlinearity in working hours, we include dummy variables of maternal working hours into our analysis. It is evident that, although the impact of maternal working hours on the z-score of BMI might be nonlinear, the estimates are not significant (see Table A2.2 in the Appendix).[13] These results thus do not either provide evidence of significant nonlinear effects of maternal working hours on child fatness.

2.5.2 Does grand-parenting really matter?

In China, the involvement of grandparents in the upbringing of their grandchildren is a topic of much public debate (see also Chen et al., 2011). Considering the important role of grand-parenting in China and its potential substitution of maternal child care when mothers are employed, we investigate how childcare of 3-6 year-old child by grandmothers associates with child adiposity among employed mothers. We focus on children aged 3-6 year as information on time input of childcare is only available for children in this age group. Furthermore, the demand for external childcare like grand-parenting is

[13] Alternatively, we also checked the nonlinearity nexus between maternal working hours and childhood obesity by using maternal working hours and its squared as well as cubic terms. The conclusions are the same.

most probably much larger for these younger children. Considering the possible nonlinearities in grandmother childcare hours (GCH), we also use dummy variables of weekly childcare hours (no childcare as the reference group, $0<GCH<6$, $6 \leq GCH<20$ and $GCH \geq 20$). Results indicate that grandmother's childcare hours are generally negatively associated with z-scores of child BMI, but the estimates are statistically insignificant (see Table A2.3). As our estimation is based on a relatively small sample size (observations=169), power is obviously limited. The results may suggest, however, that such informal childcare by grandmothers might have beneficial effects and could be an effective counterbalance against the negative effects of childhood obesity arising from maternal employment.

2.6 Conclusions

The present study is the first to investigate the association between maternal employment and child adiposity in China while taking into account child, family, and socioeconomic characteristics. The analysis is based on a large 9-province survey, the China Health and Nutrition Survey (CHNS), which has been successfully administered for several waves and is subject to strict quality control strategies (Tudor-Locke et al., 2003). Although the detailed data it provides on dietary patterns and child physical activity enable direct analysis of maternal employment's impact on diet and physical activities, even after distinguishing between rural and urban households, we find no relation between maternal employment and the objective measures of childhood obesity. Furthermore, maternal employment does not appear to be related to either diet or children's physical activity.

Some limitations obviously deserve mention. First, our analysis is cross-sectional, thereby rendering a causal analysis impossible. Moreover, with regard to physical and sedentary activities (for those 6 years and older), we use self-reported data, which could produce biased reports of the time spent on physical activities and the intensity of participation (Hussey et al., 2007). In addition, we use Western growth charts, which might give rise to biases in evaluating central childhood obesity (as measured by waist circumference) in China. Finally, our analysis is sometimes hindered by relatively small sample sizes (and thus large standard errors) – especially when taking a more differentiated look at subsamples.

Nevertheless, our results for China are well in line with recent empirical evidence for Europe (Greve, 2011; Gwozdz et al., 2013) and provide further evidence that maternal employment may not be detrimental to child obesity. In fact, our results show that, if anything, maternal employment may lower levels of childhood obesity, a finding tentatively explainable by the fact that, in China, the main resource for informal child care is grandparents, who are likely to provide a high quality of care.

Chapter 3 A Fresh Look at Calorie-Income Elasticities in China

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Abstract

In this paper, we use data from the 1991 to 2009 China Health and Nutrition Survey (CHNS) to analyze how income in China is related to calorie intake. Specifically, employing a variety of parametric, nonparametric, and semiparametric methods, we estimate calorie-income elasticities for adults aged 18-60. Our main finding is that the elasticities, although small, are generally positive, ranging from 0.006 to 0.019. In addition, although the parametric estimates reveal a slight nonlinear relation between income and calorie intake, the nonparametric and semiparametric results point to no clear nonlinearity.

Keywords: Income; calorie-income elasticity; China

JEL Classification Code: C14, D12, O1

3.1 Introduction

From 1990 to 2011, the per capita annual disposable income of Chinese urban residents increased markedly from 1510 yuan to 21810 yuan, respectively, while the per capita annual net income of rural residents rose from 686 yuan to 6977 yuan (National Bureau of Statistics of China, 2012). Yet even though Chinese income levels have increased substantially and fewer people suffer from undernourishment than one generation ago (Barrett, 2010), the *State of Food Insecurity in the World 2012* reports that 158 million Chinese are still undernourished (FAO, WFP, & IFAD, 2012). Moreover, in 2011, 122 million Chinese were still living in poverty (National Bureau of Statistics of China, 2012). At the same time, the pace of a nutritional shift from plant foods to animal foods in China has been accelerating (Ge, 2011).

It is this background that has spurred research on the effects that income changes in China are having on food security, or more specifically, on calorie intake. Knowing the size of the calorie-income elasticities is potentially useful to policy makers because it could indicate the effectiveness of income-mediated policies aimed at combating food insecurity. Yet despite the large body of literature on this topic (in China and elsewhere), the magnitudes of the estimated elasticities deviate substantially. In the eight such studies for China of which we are aware, the estimated calorie-income elasticities range from -0.65 to 1.34. In other countries variation is also large, leading Ogundari and Abudulai (2013) to comment that “the debate on the calorie-income nexus appears to be unresolved” (p.119).

The aim of this paper is to take a comprehensive look at calorie-income elasticities in China using data from the China Health and Nutrition Survey (CHNS). In doing so, we address some of the main methodological challenges encountered in estimating such elasticities. We apply a wide set of estimation techniques, including parametric, non-parametric and semi-parametric methods for cross-sectional and panel data, to explore possible nonlinearities in the nexus between income and calorie intake. Within such analysis, the identification of nonlinear calorie-income relations is particularly important because the impact of income on calorie intake may be influenced by the actual intake level (Salois et al., 2010). To our knowledge, only Meng and Gong (2009) have succeeded in exploring nonlinear relations among urban Chinese through the use of semiparametric techniques. In addition, recognizing that failure to control for unobserved effects related to income or prices might also bias results (Behrman and Deolalikar, 1990), we take such unobservables into account by estimating both parametric and semiparametric fixed-effects models. The results from this wide methodological spectrum, which includes multiple specifications and robustness tests, indicate that calorie-income elasticities are positive but small, implying that households are quite successful in maintaining calorie levels constant as income varies.

The remainder of the study is arranged as follows: Section 3.2 reviews the relevant literature on this topic, after which Section 3.3 outlines the theoretical background. Section 3.4 describes the data and methods, and Section 3.5 reports the empirical results, including those for several robustness tests. Section 3.6 concludes the paper.

3.2 Previous research

Several studies (summarized in Table 3.1) estimate calorie-income elasticities in China.[14] One of the first to show a low calorie-income elasticity is that of Guo et al. (2000), who focus on 20- to 45-year-olds using 1989 to 1993 data from the China Health and Nutrition Survey (CHNS). Specifically, using predicted log income and squared log income as income measures, they identify a negative calorie-income elasticity in 1989 that increased to about 0.02 by 1993. A similar study by Meng and Gong (2009), based on 1986–2000 data from the China Urban Household Income and Expenditure Surveys (CUHIES), transforms food expenditure information into calorie availability data and uses per capita expenditure as a proxy for income. Using different estimation techniques (OLS, (instrumental variable) IV, and semiparametric methods), the authors find that calorie-income elasticities vary greatly – between -0.124 and 0.546. Huang and Gale (2009), however, applying a log-log-inverse form of the Engel function to 2002 – 2005 survey data for urban households, suggest that calorie-income elasticities range between -0.01 and 0.21. Zhong et al. (2012), using 1991–2009 cross-sectional and panel data from the CHNS, point to even smaller calorie-income elasticities, ranging from 0.039 to 0.045. Further evidence for these relatively low calorie-income elasticities is provided by Lu and Luhrmann (2012), whose OLS and fixed-effects estimates for 1989–2006 data from the same

[14] Although they do not actually calculate calorie-income elasticities, a selection of other studies (not reviewed here) address the relation between income and different measures of food security and food consumption. Wang (2010), for example, shows that income significantly affects per capita food consumption, while Li and Yu (2010) demonstrate that individual net income can significantly increase self-reported satisfaction for food consumption and animal protein consumption. On the local level, Li and Shangguan (2010) suggest that net income is positively associated with individual energy intake in rural Shaanxi, while Nie et al. (2010) find that per capita income has only a small positive impact on household food expenditure in rural Ningxia.

dataset pinpoint them at approximately 0.08 for agricultural households and 0.09 for nonagricultural households.[15] Likewise, Jesen and Miller (2008), using data on poor households from two Chinese provinces, identify a calorie-income elasticity of 0.028 in Gansu and 0.031 in Hunan province.

Table 3.1 Summary of recent studies on calorie-income elasticity in China

Authors (year)	Data sources	Data duration	Area type	Calorie indicator	Income indicator	Outcomes
Guo et al. (2000)	CHNS	1989-1993	urban, rural	per capita energy intake	predicted per capita household income	Probit: -0.55-1.34 IV: -0.65-0.60
Du et al. (2004)	CHNS	1989-1997	urban, rural	per capita energy intake	predicted per capita household income	-
Jesen and Miller (2008)	3-wave field survey data	2006	urban, rural	percentage change of meat intake	percentage change of household income from work	Gansu: 0.028 Hunan: 0.031
Meng and Gong (2009)	CUHIES	1986-2000	urban	per capita calorie demand	per capita expenditure	OLS: 0.29-0.45 IV: 0.039-0.53 SOLS: 0.047-0.546 SIV: -0.124-0.5
Huang and Gale (2009)	China Urban Household Survey	2002-2005	urban	per capita energy intake	per capita household income	OLS: -0.01-0.21
Bishop et al. (2010)	CHNS	1991-2004	urban, rural	per capita calorie consumption	household income	0
Zhong et al. (2012)	CHNS	1991-2009	urban, rural	per capita energy intake	per capita household income	OLS: 0.042-0.045 PD: 0.039-0.041
Lu and Luhrmann (2012)	CHNS	1989-2006	urban, rural	per capita calorie intake	household income	OLS:0.002-0.004 IV: 0.05-0.09 FE: 0.005-0.008

Note: CUHIES= China Urban Household Income and Expenditure Surveys; (S)OLS= (semiparametric) ordinary least squared estimate; (S)IV =(semiparametric) instrumental variable estimate; PD means estimates based on panel data (specific estimation methods not reported); "–"= negative relationship; "0"= elasticity equal zero.

[15] Interestingly, when weather shocks and marginal income tax rates are introduced as income instruments for agricultural versus nonagricultural households, the calorie-income elasticities increase to about 0.119 and 0.152, respectively (Lu and Luhrmann, 2012).

The general observation from the previous research is that estimated elasticities vary substantially, even among studies using the same dataset. Thus, the choice of methodology is important. One major challenge in estimating calorie-income elasticities is the identification of nonlinear relationships between income and calorie intake (see Subramanian and Deaton, 1996). In most previous studies, nonlinearity in the calorie-income nexus is examined using common parametric approaches, such as the introduction of squared log-transformed income terms (Guo et al., 2000), an inverse income term (Huang and Gale, 2009), higher order of income terms (Lu and Luhrmann, 2012), or interaction terms for income groups and prices (Zhong et al., 2012). Yet if the underlying assumptions (such as normality) do not hold, parametric estimates of calorie-income elasticities may be biased. To our knowledge, only one study (Meng and Gong, 2009) uses semiparametric methods to explore a potential nonlinear calorie-income relation. The extant research also tends to estimate elasticities for men and women separately under the assumption of possible gender-specific differences in income's effect on calorie intake, and some authors have indeed shown that elasticities are larger for women than for men (e.g., Lu and Luhrmann, 2012). Lu and Luhrmann (2012) also examine the potential differences in calorie-income elasticities between agricultural and nonagricultural households, but the calorie-income elasticity magnitudes remain similar even when IV estimates are used.

In this paper, we extend the previous research in three ways:

First, to account for potential nonlinearities in the calorie-income relation, we employ a spectrum of methods that includes traditional parametric approaches (a log-log squared model (LLS) and a log-log inverse model (LLI)[16]), as well as nonparametric and semiparametric techniques based on cross-sectional and panel data.

Second, given the nature of the CHNS data, we are able to control for a very comprehensive set of individual, household, and community characteristics, including reliable measures of BMI. This latter is important because body size and body composition are determinants for calorie requirements (James and Schofield, 1990), so omitting weight and height measures may cause overestimation of calorie-income elasticities (Meng and Gong, 2009). We account for unobservable characteristics by using both parametric and semiparametric fixed-effects methods.

Third, to determine whether elasticities vary among different groups, we estimate them separately for groups of individuals that require different calories based on the most updated recommended dietary intakes (RDIs) in the *2011 Chinese Dietary Guideline* (Chinese Nutrition Society, 2011, p.215).

3.3 Theoretical framework

Our analysis of the impact of income on food security is based on a theoretical model developed and detailed by Blaylock and Blisard (1995), which assumes that personal utility is a function of food security (FS) and health status (HS):

$$U = U(FS, HS), U' > 0, U'' < 0 \qquad (1)$$

[16] A detailed discussion of these models is available in Haque (2005).

In this model, utility is maximized subject to a number of constraints, including a health status function and the food security production function of each household member:

$$FS = \varphi(X_{hc}, X_{qf}, Y) \qquad (2)$$

where X_{hc} denotes human capital, X_{qf} represents qualitative factors emanating from social interactions (Blaylock and Blisard, 1995),[17] and Y represents income levels. Food security is also improved by the availability and use of health environments and services (including safe water, electricity, sanitation facility, medical care and other health services) (Ruel et al., 2008), and is directly influenced by the price of food (Charles et al., 2010; Swinnen and Squicciarini, 2012). We therefore extend our model to include household health and environmental factors, as well as community food prices:

$$FS = F(X_{hc}, X_{qf}, X_h, X_c, Y) \qquad (3)$$

where X_h denotes the household-level factors influencing food security (e.g., availability of health services) and X_c represents the community-level factors (e.g., food prices). Our major interest is in evaluating the impact of income on household food security as captured by calorie intake.

[17] Proxies of qualitative factors usually include urban/rural location variables reflecting possible heterogeneity in domestic food production patterns, as well as ethnicity variables capturing cultural variety (Blaylock & Blisard, 1995).

3.4 Data and methods

3.4.1 Study design

The study data are taken from the China Health and Nutrition Survey (CHNS), an ongoing Sino-American project investigating the potential changes in demography, health, and nutrition in China. The survey sample covers nine provinces[18] with a total of 26000 individuals from 4400 households.[19] A total of nine survey waves have been conducted to date, the first in 1989 and the most recent in 2011. Data are collected on the community, household, and individual level, with household samples in each province drawn using multistage, random cluster sampling (for further details, see Popkin et al., 2010).

In this present study, we use a sample of 18- to 60-year-olds from 1991 to 2009. After dropping the top and bottom 1% of the household per capita income distribution (inflated to 2011), as well as any missing values on individual calorie intake and other covariates, the final sample size is 45398 individuals (see Appendix A3.1 for the descriptive statistics).

3.4.2 Study variable definitions

Individual calorie intake. The CHNS data are notable for the high quality of their nutritional and health information for both households and individuals (Mangyo, 2008). For example, the survey collects individual calorie intake (kcal) for 3 consecutive days for each household and individual, asking all respondents directly about all food consumed inside and outside the home on a 24-hour recall

[18] These nine provinces are Heilongjiang and Liaoning, two northeastern provinces with higher industrial levels; Jiangsu and Shandong, two eastern industrialized provinces; Henan, Hubei, and Hunan, three central provinces dominated by agriculture; and Guangxi and Guizhou, two less economically developed provinces in southwest China. Thus, these selected provinces differ with regards to geographical and economic conditions and are regionally representative.

[19] Detailed information is available at http://www.cpc.unc.edu/projects/china.

basis. In our study, therefore, we use a 3-day average individual calorie intake as a measure of food security. The advantages of using calories as a measure of food security include its being arguably the most accurate measure for individuals (Hoddinott, 1999) and the usefulness of the information it provides about differences in intrahousehold food security (Smith et al., 2006).

Income. Our income measure is household per capita income (i.e., total household income divided by household size) inflated to 2011. In the CHNS questionnaire, such income is attributable to nine sources: farming, gardening, livestock/poultry, fishing, business, subsidies, retirement income, nonretirement earnings, and other.[20]

Additional independent variables are categorized into three groups: individual, household, and community characteristics.

Individual characteristics. Our analysis addresses six individual characteristics: age, gender, years of schooling, activity level, location (urban/rural), and availability of medical insurance. The gender dummy equals 1 if the individual is a male, 0 otherwise; the location dummy equals 1 if the individual lives in an urban area, 0 otherwise; and the medical insurance dummy equals 1 if the individual has medical insurance, 0 otherwise. Activity level is measured on a 3-point scale: 1 =light, 2 =moderate, and 3 =heavy.

Household characteristics. Our models include four household variables: household size, availability of safe drinking water, sanitation, and electricity. The safe drinking water variable equals 1 if the household's drinking water source is

[20] It is worth noting that calorie-income elasticities calculated using total expenditure as measure of income are usually significantly higher than those based on household income (Ogundari & Abdulai, 2013). This difference should be kept in mind when comparing our results with those of other studies using expenditure as the income measure.

a water plant or ground water more than 5 meters deep, 0 otherwise. The sanitation variable equals 1 if the household can access in-house or outside flushing of toilet facilities, 0 otherwise. The electricity variable equals 1 if electric facilities are available for the household, 0 otherwise.

Community characteristics. Because the CHNS collects unique data on community-level commodity prices, we are able to control for the prices of 20 foods: rice (the commonest type), bleached flour, unbleached flour, corn flour, millet, sorghum, rapeseed oil, soybean oil, peanut oil, sugar, eggs, the most commonly eaten vegetables, pork, chicken, beef, mutton, domestically fresh whole milk, domestically whole powered milk, fish, and beancurd. It should be noted that the CHNS reports three types of price information: free market prices, state-owned store prices, and authority price records (Du et al., 2004; Guo et al., 2000). However, since 1989, state-owned stores have been gradually replaced by free markets and supermarkets, so most food is now purchased on the free market (Du et al., 2004). We therefore use market prices, inflated to 2011.

3.4.3 Analytical methods

Calorie-income elasticity: parametric models. To estimate the effect of income on calorie intake, we begin by estimating functions of the following form:

$$logCI = \alpha_0 + \alpha_1 logINC + \alpha_2 I + \alpha_3 H + \alpha_4 C + \alpha_5 T + \varepsilon \quad (4)$$

where *logCI* is log-transformed individual 3-day average calorie intake, and *logINC* is log-transformed household per capita income. *I* is a matrix of individual controls, *H* is a matrix of household controls, and *C* is a matrix of community controls. *T* is a matrix of year dummies with 1991 as the reference year, ε is a matrix of random disturbance errors, and α_1 is the key coefficient of interest whose magnitude is the calorie-income elasticity.

Given the possible nonlinear nexus of income and calorie intake, we also use two more flexible specifications in this parametric framework: a log-log squared model (LLS, log-transformed calorie intake and income with squared log-transformed income) and a log-log inverse model (LLI, log-transformed calorie intake and income with inverse income). Such treatment is similar to that of Skoufias et al. (2009). The detailed specifications of these two models are as follows:

$$logCI = \theta_0 + \theta_1 logINC + \theta_2 (logINC)^2 + \theta_3 I + \theta_4 H + \theta_5 C + \theta_6 T + \varepsilon \quad (5)$$

$$logCI = \delta_0 + \delta_1 logINC + \delta_2 / INC + \delta_3 I + \delta_4 H + \delta_5 C + \delta_6 T + \mu \quad (6)$$

INC in model (6) is household per capita income; the other parameters are the same as in model (4).

The corresponding calorie-income elasticities of models (5) and (6) are shown in models (7) and (8), respectively:

$$\partial \mathrm{logCI} / \partial \mathrm{logINC} = \theta_1 + 2\theta_2 logINC \quad (7)$$

$$\partial \mathrm{logCI} / \partial \mathrm{logINC} = \delta_1 - \delta_2 / INC \quad (8)$$

In these models, if δ_2 or θ_2 are significant, calorie-income elasticities vary with income level. For instance, in model (8), if $\delta_1>0$ and $\delta_2<0$, then calorie-income elasticities decrease as income increases; if $\delta_1=\delta_2/INC$, they equal 0; and if $\delta_1<\delta_2/INC$, they become negative. However, when $\delta_2=0$, the calorie-income elasticity becomes a constant equal to δ_1, which neither equals 0 nor changes sign when δ_1=0 (see Huang and Gale, 2009, for a detailed discussion on the advantages of LLI models).

We perform our OLS estimates on models (4), (5), and (6); however, it is worth noting that such estimations are only valid if

$$E(\varphi'\varepsilon) = 0, \qquad \varphi = \varphi(logINC, I, H, C) \qquad (9)$$

If unobservable heterogeneity (e.g., individual food preferences and eating habits or social norms) is correlated with income, then OLS estimates of the calorie-income elasticities will be biased (Lu and Luhrmann, 2012). Another potential issue is measurement error, a problem, however, that is likely to be minimal in our study because the quality of the income and calorie data in the CHNS is high.

The estimates may also be biased if the analysis fails to account for community, household, and individual fixed effects (Behrman and Deolalikar, 1990), so we also employ individual-level fixed effect models to control for community, household, and individual unobservables. These specifications include both one-way and two-way fixed-effects models:

$$logCI_{ict} = \gamma_0 + \gamma_1 logINC_{ict} + I_{ict}\gamma_2 + H_{ct}\gamma_3 + C_{ct}\gamma_4 + \alpha_i + \varepsilon_{ict} \qquad (10)$$

$$logCI_{ict} = \gamma_0 + \gamma_1 logINC_{ict} + I_{ict}\gamma_2 + H_{ct}\gamma_3 + C_{ct}\gamma_4 + \gamma_5 T + \alpha_i + \varepsilon_{ict} \quad (11)$$

where $logCI_{ict}$ is the 3-day average calorie intake of individual i in community c at time t and $logINC_{ict}$ is household per capita income of individual i in community c at time t. I_{ict} is a matrix of individual covariates, H_{ict} is a matrix of household level covariates, and C_{ct} is a matrix of community level covariates. T denotes time effects, α_i is an individual time-invariant fixed effect, ε_{ict} is the idiosyncratic error term, and γ_1 is the key coefficient of interest. We also take into account clustering at the individual level.

Calorie-income elasticity: nonparametric model. When assumptions such as normality do not hold, parametric estimates will be inefficient (DiNardo and Tobias, 2001). Moreover, rather than estimating at a single point, it is important to explore the full range of calorie-intake responses to income (Gibson and Rozelle, 2002). One possible way to take nonlinearity into account is to use nonparametric estimates, which are more flexible primarily because the functions to be estimated are based on pliable assumptions (DiNardo and Tobias, 2001).

The model we estimate is a univariate nonparametric model:

$$y_i = m(x_i) + \varepsilon_i, \varepsilon_i \sim iid(0, \sigma_\varepsilon^2) \quad (12)$$

where y_i denotes 3-day average individual calorie intake and $m(x_i)$ is an unknown functional form of household per capita income. Because of the underlying biases stemming from kernel smoothing estimates, in this study, we employ the locally weighted scatterplot smoothing (LOWESS) developed by Cleveland (1979), which uses changeable bandwidths and mitigates the possible biases associated with boundary problems.

Calorie-income elasticity: semiparametric model. Although nonparametric methods help us to identify potentially nonlinear calorie-income relations, their most evident limitation is the dimensionality that inhibits the introduction of control variables (DiNardo and Tobias, 2001). To solve this obstacle, we employ a semiparametic approach using a partially linear model (PLM):

$$y_i = X_i\beta + \lambda(z_i) + \varepsilon_i, E(\varepsilon_i | X_i, z_i) = 0, i = 1, \cdots, N \quad (13)$$

where X_i is a matrix of explanatory variables, and z_i is the variable of household per capita income with unknown functional form.

For this model, we use the Robinson (1988) double residual estimator with clustering at the community level, which first takes the conditional expectation on z_i:

$$E(y_i|z_i) = E(X_i|z_i)\beta + \lambda(z_i) + E(\varepsilon_i|z_i), i = 1, \cdots, N \quad (14)$$

Subtracting (13) from (14) then yields

$$y_i - E(y_i|z_i) = (X_i - E(X_i|z_i))\beta + \varepsilon_i, i = 1, \cdots, N \quad (15)$$

$E(y_i|z_i)$ and $E(X_i|z_i)$ are first estimated using nonparametric techniques and then replaced into model (15), so that β can be estimated consistently. Finally, $\lambda(z_i)$ is estimated by regressing (16) nonparametrically (Verardi and Debarsy, 2012):

$$y_i - X_i\hat{\beta} = \lambda(z_i) + \varepsilon_i, i = 1, \cdots, N \quad (16)$$

Semiparametric fixed-effects model. Instead of traditional fixed-effects techniques, we employ Baltagi and Li's (2002) series estimator of partially linear panel data models with fixed effects, which is better able to identify an unknown or complicated nexus of two potential variables (Libois and Verardi, 2013). The general panel-data semiparametric model is as follows:

$$y_{it} = X_{it}'\gamma + f(z_{it}) + \alpha_i + \varepsilon_{it}, i = 1, \cdots, N; t = 1, \cdots, T, T \ll N \ (17)$$

where X_{it} is a matrix of explanatory variables assumed to be exogenous, z_{it} represents strictly exogenous variables, α_i denotes time-invariant fixed effects, and ε_{it} is the idiosyncratic error term. In this semiparametric fixed-effects approach, a series of $p^k(z)$ (the first k terms of a sequence of functions) is the approximation of *f(z)* (Libois and Verardi, 2013). Again, we account for clustering at the individual level.

3.5. Results

3.5.1 Descriptives

Our descriptive statistics on income and calorie-intake changes for different populations show that household per capita income (inflated to 2011) has increased sharply, from 3117 yuan in 1991 to 10898 yuan in 2009 (see Table A3.2). This increase is particularly evident in rural areas, although rural levels are still substantially lower than those in urban areas.

In terms of individual calorie intake, however, a significant decline is observable, from an average of approximately 2742 kcal in 1991 down to about 2251 kcal in 2009 (see Table A3.3). This decline is discernible in both rural and urban areas, and among both men and women. Declines in calorie intake are also detectable in the different activity levels, although the greatest decline– a total of 588 kcal between 1991 and 2009 – occurs among individuals whose activity level is heavy (see Table A3.4). This finding is most probably a result of the rapid economic and social transition – and in particular, the accelerating process of urbanization and transition away from a predominantly agricultural economy – which has led to a decline in adult occupational intensity (Monda et al., 2007). A comparison of actual calorie intake with the RDIs from the *2011 Chinese Dietary Guidelines* reveals that the calorie intake of 50- to 60-year-old females is consistently higher than the RDIs criteria, while in the 18- to 50-year-old age group, only the intake of females with a light activity level exceeds the RDIs requirement (see Table A3.5). It is particularly interesting, however, that in most other activity-level groups, the RDIs criteria are not being met (with the exception of males in the light activity-level group). It is therefore important to take gender and age-specific activity levels into account when analyzing the effects of income change on calorie intake.

3.5.2 Calorie-income elasticity: linear relations of parametric estimates

OLS estimates. The regression results from the OLS estimates (see Table 3.2) indicate that household per capita income is significantly correlated with individual calorie intake, and that calorie-income elasticities are relatively small, ranging from -0.045 to 0.011. These elasticities do increase slightly, however, when year and provincial dummies as well as controls for community-level food prices are added into the specification. We also note in passing (results not shown in the table) that higher activity levels correspond to higher calorie intake but that education and household size are significantly negatively related to individual calorie intake. [21]

Table 3.2 OLS estimates of calorie-income elasticity

Variables	(1)	(2)	(3)	(4)
logINC	-0.045***	-0.013***	0.006***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	8.125***	8.086***	7.513***	7.681***
	(0.014)	(0.022)	(0.038)	(0.054)
N	45398	45398	45398	45398
Adj. R^2	0.017	0.118	0.156	0.177

Note: (1) only contains household per capita income (inflated to 2011). (2) contains household per capita income (inflated to 2011), age, education level, and dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2=moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity. (3) contains the same regressors as (2) but introduces the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. (4) contains the same regressors as

[21] As some variables are potentially endogenous (e.g. education), we also estimated the regressions excluding these variables and find very similar results.

(3) but introduces a province dummy(with Liaoning as the base province) and a year dummy (with 1991 as the base year). Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 3.3 presents the results separately for men and women and also based on different RDIs levels for the 18–50 age group. The results indicate that calorie-income elasticities remain small and are sometimes even negative, although interestingly, among 18- to 50-year-olds, the calorie-income elasticity is significantly positive for males with an RDIs under 2400 kcal (see model 1 in Table 3.3) but negative for males with an RDIs over 3200 kcal (see model 4 of Table 3.3). This finding suggests that males with a heavy activity level may decrease their calorie intake when income rises. Table 3.4 presents corresponding results for the 50-60 age group, for which the elasticities again remain small.

Table 3.3 OLS estimates of calorie-income elasticity based on RDIs (18- to 50-year-olds)

Variables	Male				Female			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
logINC	0.0161^{***}	0.0004	0.0005	-0.0070^{*}	0.0075^{**}	0.0012	-0.0000	-0.0031
	(0.004)	(0.001)	(0.001)	(0.004)	(0.003)	(0.001)	(0.001)	(0.004)
Constant	7.7384^{***}	7.7983^{***}	7.9657^{***}	8.4394^{***}	7.5843^{***}	7.6642^{***}	7.8093^{***}	8.1560^{***}
	(0.094)	(0.024)	(0.032)	(0.129)	(0.085)	(0.021)	(0.031)	(0.122)
N	6644	3018	3826	3389	7738	2390	3729	4002
Adj. R^2	0.049	0.000	0.007	0.041	0.062	0.011	0.006	0.037

Note: All models contain household per capita income (inflated to 2011), education level, and dummies for urban residence (1=urban, 0=rural), activity level (1=light, 2=moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. They also contain a province dummy (with Liaoning as the reference province) and a year dummy (with 1991 as the base year). (1)-(4) are based on different RDIs thresholds of calorie intake for males; (5)-(8) are based on different RDIs thresholds of calorie intake for females. Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

To assess whether calorie-income elasticities vary across the conditional distribution of calories, we also run quantile regressions (see Table 3.5). As the first panel of Table 3.5 shows, in the 18-50 age group, calorie-income elasticities are insignificant, regardless of different thresholds in the calorie-intake distribution. Among the 50- to 60-year-olds, however, the calorie-income elasticities are mostly significantly positive, albeit small (see Table 3.5, second panel). Thus, there is little evidence that elasticities differ much across the calorie distribution, especially given that all elasticities remain close to zero.

Table 3.4 OLS estimates of calorie-income elasticity based on RDIs (50- to 60-year-olds)

Variables	Male				Female			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
logINC	0.0116*	-0.0023	0.0023	-0.0124	0.0062	0.0003	-0.0005	0.0058
	(0.006)	(0.002)	(0.002)	(0.008)	(0.006)	(0.001)	(0.001)	(0.005)
Constant	7.5786***	7.7937***	7.8622***	8.3384***	7.3062***	7.5985***	7.6101***	7.9329***
	(0.146)	(0.048)	(0.061)	(0.208)	(0.159)	(0.025)	(0.038)	(0.149)
N	2131	920	1140	1018	1940	409	738	2366
Adj. R^2	0.041	0.000	0.000	0.040	0.026	0.020	0.016	0.025

Note: All models contain household per capita income (inflated to 2011), education level, and dummies for urban residence (1=urban, 0=rural), activity levels (1=light, 2=moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. They also contain a province dummy (with Liaoning as the reference) and a year dummy (with 1991 as the base year). (1)-(4) are based on different RDIs thresholds of calorie intake for males; (5)-(8) are based on different RDIs thresholds of calorie intake for females. Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 3.5 Quantile estimates of calorie-income elasticity (18-60-year-olds)

Variables	All (18≤&<50)			Male (18≤&<50)			Female (18≤&<50)		
	25%	50%	75%	25%	50%	75%	25%	50%	75%
logINC	0.003	0.002	0.002	0.008**	0.0006	0.0003	0.0007	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Constant	7.278***	7.608***	7.779***	7.461***	7.798***	7.912***	7.285***	7.565***	7.791***
	(0.060)	(0.049)	(0.053)	(0.087)	(0.067)	(0.077)	(0.077)	(0.069)	(0.082)
N	34736	34736	34736	16877	16877	16877	17859	17859	17859
Pseudo R^2	0.066	0.061	0.058	0.060	0.055	0.058	0.085	0.078	0.074
Variables	All (50≤&<60)			Male (50≤&<60)			Female (50≤&<60)		
	25%	50%	75%	25%	50%	75%	25%	50%	75%
logINC	0.009	0.010**	0.012***	0.006	0.016***	0.013	0.012	0.015***	0.014**
	(0.006)	(0.004)	(0.004)	(0.007)	(0.006)	(0.008)	(0.009)	(0.005)	(0.007)
Constant	7.207***	7.495***	7.675***	7.336***	7.651***	7.757***	7.239***	7.553***	7.796***
	(0.120)	(0.107)	(0.089)	(0.167)	(0.153)	(0.145)	(0.158)	(0.134)	(0.154)
N	10662	10662	10662	5209	5209	5209	5453	5453	5453
Pseudo R^2	0.042	0.039	0.039	0.040	0.034	0.041	0.037	0.039	0.037

Note: All models contain household per capita income (inflated to 2011), education level, and dummies for urban residence (1=urban, 0=rural), activity level (1=light, 2=moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. Bootstrapped standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Fixed-effect (FE) estimates. The FE estimates of calorie-income elasticity (see Table 3.6) indicate that income has a consistently and significantly positive relation with individual calorie intake. The estimates are also slightly larger than those in the OLS analysis (see Ogundari and Abudulai, 2013).

Table 3.6 FE estimates of calorie-income elasticity

Variables	FE	FE_C	FE_TW
logINC	0.019***	0.019***	0.019***
	(0.005)	(0.006)	(0.006)
Constant	7.854***	7.854***	7.239***
	(0.115)	(0.122)	(2.375)
N	7960	7960	7960
R^2	0.032	0.032	0.033

Note: The estimated sample is restricted to 2000, 2004, 2006, and 2009. All models contain household per capita income (inflated to 2011), age, household size, activity level (1=light, 2= moderate, and 3=heavy), and the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. FE_C=fixed effect estimate with individual-level clustered standard errors; FE_TW = two-way fixed effects with time effects (adding a year dummy with 2000 as the base year). Individual-level clustered standard errors are in parentheses for FE estimates with time effects; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

In sum, therefore, when income is treated linearly, the calorie-income elasticities in our analysis are negligible, irrespective of whether estimated using OLS (elasticities ranging from 0.006 to 0.011), quantile regressions (elasticities ranging from 0.002 to 0.012), or fixed-effects models (elasticities approximately equal to 0.019). Our findings thus mirror those of other studies on this topic that use CHNS data (Bishop et al., 2010; Lu and Luhrmann, 2012; Shankar, 2010; Zhong et al., 2012).

3.5.3 Calorie-income elasticity: nonlinear relations

LLS model and LLI model estimates. We further examine possible nonlinearities in the relation between income and calorie intake by estimating both LLS and LLI models. Results lend some support that nonlinearities in the calorie-income nexus exist (see Table A3.6 in the appendix). In the results given in Table 3.7, two points are worth noting: (1) in both models, elasticities are significantly positive, although the magnitudes differ slightly (LLS: ranging from 0.004 to

0.023; LLI: ranging from 0.008 to 0.017); (2) in both models, calorie-income elasticities increase as household per capita income increases from the bottom 10% to the top 90%.

Table 3.7 Calorie-income elasticities for LLS and LLI models

Income	10%	25%	50%	75%	90%
Loghhinc11+ squared loghhinc11 (LLS)					
(1) OLS	0.0044	0.0090	0.0138	0.0184	0.0226
Loghhinc11+ inverse hhinc11 (LLI)					
(2) OLS	0.0082	0.0123	0.0146	0.0158	0.0165

Note: LLS =regression model logci-loghhinc11+squared loghhinc11; LLI =regression model logci-loghhinc11+inverse hhinc11. The OLS estimates include age, education level, and dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2= moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. They also include a year dummy (with 1991 as the base year). The elasticities in models (1) and (2) are -0.0496+0.0076*loghhinc11 and 0.0173-11.2269*(1/hhinc11), respectively.

Nonparametric estimates. Because traditional parametric methods can lead to biases, we further estimate elasticities using a nonparametric approach, the LOWESS smoothing method performed on three different bandwidths (0.2515, 0.1258 and 0.503, respectively, based on Silverman's one, half and twice plug-in estimates[22]). As is evident from Figure 3.1 (using one plug-in estimate), the slope depicting the relation between calorie intake and income is very flat, indicating that changes in income have little effect on changes in calorie intake (at all levels of income).[23]

22 The optimal bandwidth is calculated based on $H^*=1.3643\delta N^{-0.2}\min(s, IQR/1.349)$, where H^* denotes optimal bandwidth, δ equals to 1.7188 for the Epanechnikov kernel, N designates sample size, s is standard deviation of the sample and IQR is the sample interquartile range between 75% and 25% (Cameron & Trivedi, 2005). For brevity, we only report LOWESS estimates with one plug-in, the other estimates with half and twice plug-in are available from the authors upon request.

23 For a nonparametric approach to estimating calcium/vitamin A-income elasticities in China, see Liu and Shankar (2007).

Figure 3.1: Nonparametric estimate of calorie-income elasticity: 1991–2009

Semiparametric estimates. As is clear from the semiparametric estimates in Figure 3.2, the slope of the calorie-income nexus is very similar to that of the nonparametric estimation; that is, the slope of the calorie-income relation is consistently stable across all levels of household per capita income.

Figure 3.2: Semiparametric estimate of calorie-income elasticity (nonparametric part)

Table 3.8 Semiparametric estimates of calorie-income elasticity (parametric part, reduced form)

Variables	Coefficient	Std. Error	95% Conf. Interval
Age	-0.001***	(0.000)	[-0.0013,-0.0004]
Education	-0.004***	(0.001)	[-0.0052,-0.0021]
Gender=1	0.159***	(0.003)	[0.1521,0.1651]
Urban=1	-0.012	(0.015)	[-0.0405,0.0172]
Household size	-0.009***	(0.002)	[-0.0133,-0.0046]
Activity level=2	0.019***	(0.006)	[0.0070,0.0307]
Activity level=3	0.110***	(0.009)	[0.0930,0.1276]
N		45398	
Adj. R^2		0.151	

Note: The semiparametric model contains household per capita income (inflated to 2011), age, education level, and dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2=moderate, and 3=heavy), availability of medical insurance, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. It also contains a year dummy (with 1991 as the base year). The 95% confidence intervals are in brackets; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

The parametric parts of the semiparametric estimates are reported in Table 3.8, which shows that, interestingly, education and household size are significantly and negatively correlated with individual calorie intake, although with different magnitudes. Activity levels also have a positive relation with calorie intake. These results are consistent with the parametric results reported earlier.

Semiparametric fixed-effects estimates. The nonparametric results of the semiparametric fixed-effects estimation are reported in Figure 3.3. The slope of the calorie-income relationship is slightly positive at low levels of income.

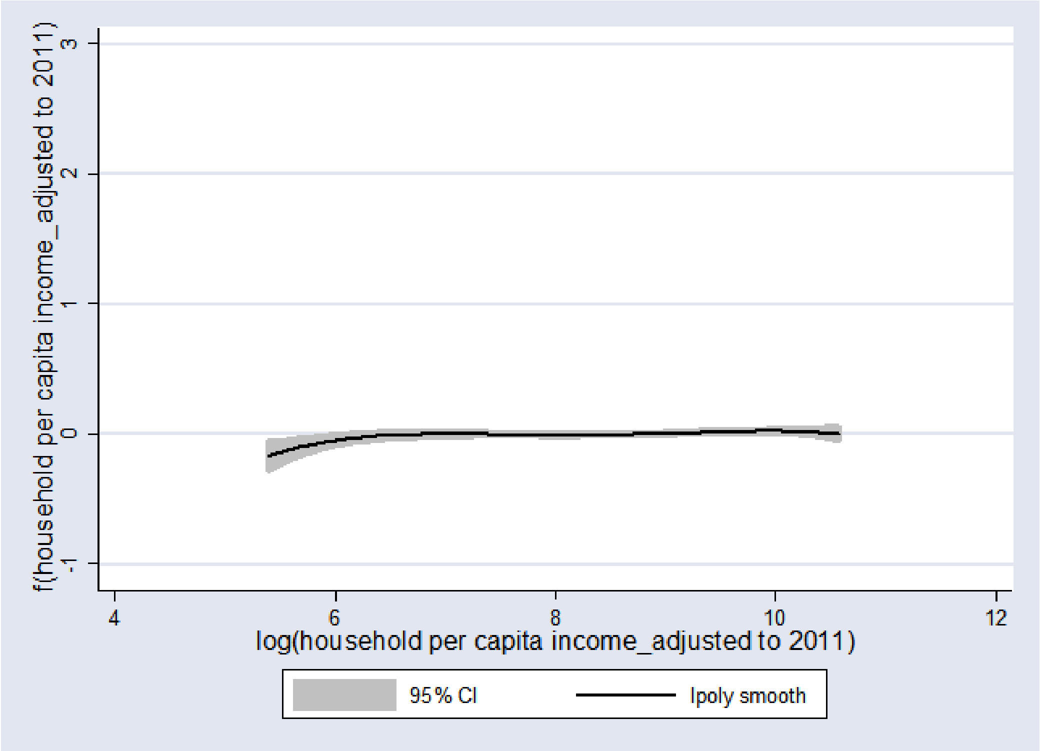

Figure 3.3: Semiparametric fixed-effects estimate of calorie-income elasticity (nonparametric prediction of income, within individual level clusters).

Nevertheless, it should again be emphasized that the shape of the relation between income and calorie intake is very similar, regardless of the methodology used. The parametric parts of the semiparametric fixed-effects estimation are listed in Table 3.9.

Table 3.9 Semiparametric fixed-effects estimates (parametric part, reduced form)

Variables	Coefficient	Std. Error	95% Conf. Interval
Age	0.142**	(0.064)	[0.0171,0.2663]
Household size	-0.004	(0.005)	[-0.0139,0.0064]
Activity level=2	-0.003	(0.014)	[-0.0300,0.0249]
Activity level=3	0.025*	(0.015)	[-0.0042,0.0546]
N		5970	
Adj. within R^2		0.024	

Note: The semiparametric fixed-effects model contains age, activity level (1=light, 2=moderate, and 3=heavy), household size, as well as the prices (in yuan per kilogram, inflated to 2011) 20 different foods in the free market. It also contains a year dummy (with 2000 as the base year) and individual-level cluster effects. Robust standard errors are in parentheses. The 95% confidence intervals are in brackets; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

3.5.4 Robustness checks

Control for BMI. As a robustness test, we introduce BMI into our estimations mainly because calorie-income elasticities might be overestimated if certain variables are omitted (Meng and Gong, 2009). As is clear from Table A3.7, income has a uniformly significant effect on calorie intake, with calorie-income elasticities ranging from -0.012 to 0.012, which is quite similar to the -0.013 to 0.012 estimated when no BMI control is present.

Control for household assets. We control for the potential impact of household assets on household food security using eight common electric appliances as proxies: VCR, TV, washing machine, refrigerator, air-conditioner, sewing machine, fan, and camera. Each variable is equal to 1 if the household has such an asset, 0 otherwise. As Table A3.8 shows, controlling for household assets does not change the estimates substantially: the calorie-income elasticities range from 0.009 to 0.013.

Control for the effects of poverty. Given Thomson and Metz's (1998) emphasis on the poor's greater vulnerability to food insecurity in the face of certain shocks to entitlement – especially income changes and food price spikes, we also estimate calorie-income elasticities explicitly for those whose income is below the mean household per capita income in our sample.[24] As columns 3 and 5 of Table A3.9 shows, the elasticities, although significant, remain small in the low income group.

3.6 Conclusions

Although controversy remains about the magnitude of calorie-income elasticities and estimates vary substantially (Ogundari and Abudulai, 2013), our comprehensive re-examination of the income-calorie intake relation provides further evidence that calorie-income elasticities are small, regardless of whether parametric, nonparametric, or semiparametric approaches are used. More specifically, these elasticities remain small even when nonlinearities are taken into account and estimated separately for rural and urban individuals, males and females, individuals requiring different calorie intake, and poorer households. In fact, any slight differences observed (depending on the methodology and sample) are small and arguably negligible, meaning that our findings are consistent with those of previous studies (Bishop et al., 2010; Lu and Luhrmann, 2012; Shankar, 2010; Zhong et al., 2012). Such small calorie-income elasticities are, prima facie, not supportive of "income growth optimism". They also suggest that households are quite successful in maintaining calorie levels constant as income varies. It should also be noted, however, that as income has risen in China, it is the demand for better food quality, food diversity, and food safety that has increased (Liu et al., 2013b; Gale and Huang, 2007), not necessarily the demand for more calories per se.

[24] In our sample, the mean household per capita income equals 6,118 yuan.

Chapter 4 Peer Effects on Childhood and Adolescent Obesity in China

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Abstract

Using data from the China Health and Nutrition Survey (CHNS), this study analyzes peer effects on obesity in a sample of 3- to 18-year-old children and adolescents in China. Even after a rich set of covariates and unobserved individual heterogeneity are controlled for, it is evident that such peer effects do indeed exist. These effects are stronger in rural areas, among individuals at the upper end of the BMI distribution, and especially among females. All else being equal, female adolescents whose peers have a higher BMI are less likely to consider themselves overweight, suggesting that peer effects may be working through changed societal bodyweight norms.

JEL Classification Codes: I10, I15, J13, C14

Keywords: Peer effects; children and adolescents; BMI; China

4.1 Introduction

Obesity is a global public health concern not only for Western countries but also for emerging countries like China (Cheng, 2012). In China, obesity among children and adolescents is increasing sharply, with a quadrupling of obesity and a 28 fold increase in overweight among 7- to 18-year-olds within just 15 years (1985–2000) (Lenton, 2008). The prevalence of abdominal obesity in children and adolescents aged 6-17 years has also increased dramatically (Liang et al., 2012): based on the International Obesity Task Force (IOTF) criterion, general obesity and overweight increased from 6.1% in 1993 to 13.1% in 2009 while abdominal obesity increased from 4.9% to 11.7% over the same period. Child and adolescent adiposity is even worse in some metropolitan cities like Beijing where, according to China's Working Group on Obesity (CWGOC), 21.7% of 2- to 18 years-olds were obese in 2004 (cited in Shan et al., 2010).

A large body of literature explores possible explanations for this rapid increase in childhood and adolescent obesity, including individual, social, economic, and environmental factors (de la Haye et al., 2011). One recent research stream examines the role of social networks on weight outcomes (see, e.g.Christakis and Fowler, 2007; Cohen-Cole and Fletcher, 2008), emphasizing the important role of peers in influencing the bodyweight of both adolescents and adults. Understanding such peer effects has particularly important implications for public policy design and interventions, primarily because, if peer effects do indeed exist, then preventing obesity in one individual could have a beneficial effect on others. That is, spillovers associated with social networks lead to a social multiplier effect (Christakis and Fowler, 2007).

This paper investigates whether similar peer effects on bodyweight exist in a sample of 3- to 18-year-old children and adolescents in China. In doing so it fills three research gaps. First, unlike the existing literature on peer effects and obesity, which is strongly dominated by research from the United States, it expands empirical investigation beyond the Western world. Such expansion is important because peer effects may well be influenced by culture, with individualistic societies being possibly less susceptible to peer effects than more collective societies (Mora and Gil, 2013). Whereas western cultures like the U.S. highlight individualism, self-autonomy, competition, and the significance of individual possessions, eastern ones like China are prone to foster cooperation, community, dependence, and relatedness (Gonzalez-Mena, 1993). In addition, Chinese children are more strongly socialized than American children, making them more likely to be vulnerable to others' opinions, judgments, and evaluations (Fung, 1999). Differences may therefore be expected between peer effects on individual weight in Western environments like the U.S. and those in Asian environments like China. Yet to the best of our knowledge, our paper is the first to analyze peer effects on childhood and adolescent weight in rural and urban China.

Second, it broadens the almost exclusive current focus on adolescents and adults by analyzing children as well. This lack of research on the young is surprising given the wide recognition in the consumer science literature that young children's consumption decisions are affected by those of their peers (Dishion and Tipsord, 2011). If such peer effects do exist, they could be especially important in that eating habits are formed at a young age (Kelder et al., 1994; Schwartz et al., 2011). Third, by allowing us to assess whether a relation exists between peer obesity and individual perceptions of weight status – on which there is as yet little evidence – our data enable closer examination than in prior studies of the mechanisms through which peer effects might work.

Overall, our results show not only that peer effects exist among Chinese children and adolescents aged 3 to 18 years but that such effects are stronger among females than among males, in rural than in urban areas, and among individuals at the upper end of the BMI distribution. Our results also support the notion that peer BMI affects individual bodyweight perceptions.

The remainder of the paper proceeds as follows: Section 4.2 reviews the relevant literature. Section 4.3 describes the identification issues for peer effects, our identification strategy, and our analysis of underlying mechanisms. Section 4.4 outlines the data and methods. Section 4.5 reports the results of the empirical analysis and robustness checks, and Section 4.6 concludes the paper.

4.2 Prior research

The relevant studies analyzing peer effects on obesity are listed in Table 4.1. The seminal study by (Christakis and Fowler, 2007) confirms the existence of a social-network multiplier effect. Using data from the 32-year Framingham Health Study (1971 to 2003), they show that adults are 57% more likely to be obese if their friends become obese. Several other studies based on the National

Longitudinal Study of Adolescent Health (Add Health) dataset also reveal a positive association between peer effects and adolescent obesity (Cohen-Cole and Fletcher, 2008; Fowler and Christakis, 2008; Halliday and Kwak, 2009; Renna et al., 2008; Trogdon et al., 2008; Yang and Huang, 2013). On the other hand, when Cohen-Cole and Fletcher (2008) use the Add Health data to replicate the findings of Christakis and Fowler (2007), their results, although they do not rule out the possibility of peer effects, suggest that community-level factors can explain a large share of the peer effect. The authors also argue that "shared environmental factors can cause the appearance of social network effects" (Cohen-Cole and Fletcher, 2008, p. 1386). Fowler and Christakis (2008), however, in a rebuttal of this study also based on Add Health data, provide further evidence for the existence of peer effects.

Renna et al. (2008) show that a higher BMI in close friends is associated with higher adolescent BMI, and adolescents are more responsive to the body weight of their same gender friends. This observation is confirmed for the U.S. by Larson et al. (2013), whose analysis of the 2010 Eating and Activity in Teens (EAT) survey in Minnesota suggests that the proportion of overweight friends is correlated with higher adolescent BMI.[25] Likewise, Halliday and Kwak (2009), using Add Health data, confirm a strong correlation between peer and individual BMI, while Trogdon et al. (2008), in a study of same-grade school peer groups, show that peer effects on adolescent weight do exist and are stronger for both individuals with a higher BMI and for females.

[25] The Eating and Activity in Teens (EAT) survey polls 2,793 adolescent respondents (with an average age of 14.4 years), approximately 46% of whom are in middle school and about 54% in high school.

Another perspective is offered by Yang and Huang (2013), whose examination of asymmetric peer effects on individual weight indicates that although individual weight gain is associated with having more friends that are obese, weight loss is not correlated with having fewer obese friends. The existence of persistent peer effects on individual weight outcomes is further confirmed by the study of Ali et al. (2012) on the peers' dynamic effects on adolescent weight, which also shows that they lead to individual weight gain. The only study that we are aware of that provides causal evidence is that of Yakusheva et al. (2014) that uses a sample of first-year college students.

Table 4.1 Summary of recent studies of peer effects on individual bodyweight

Authors (year)	Data source	Country	Targets	Peer definition	Methods	Outcomes
Christakis and Fowler (2007)	Framingham Health Study	U.S.	Adults	Self-nominated friends, siblings, spouse, and neighbors	LLM	Positive
Cohen-Cole and Fletcher (2008)	Add Health	U.S.	Adolescents	Self-nominated friends	OLS Logit	Positive
Renna et al. (2008)	Add Health	U.S.	Adolescents	Self-nominated friends	OLS/IV	Positive
Trogdon et al. (2008)	Add Health	U.S.	Adolescents	Self-nominated friends; Students within the same grade	OLS/TSLS Probit/TSLS-Probit QR	Positive
Fowler and Christakis (2008)	Add Health	U.S.	Adolescents	Self-nominated friends	OLS/FE/MCS	Positive

Halliday and Kwak (2009)	Add Health	U.S.	Adolescents	Self-nominated friends	OLS/Probit/FE	Positive
Valente et al. (2009)	In-school survey, Los Angeles	U.S.	Adolescents (11-15 yrs)	Self-nominated friends	RE-Logistic ERGM	Positive
Yakusheva et al. (2011)	The study from a private Midwestern university	U.S.	Female freshmen	Roommates	NE	Negative
Yakusheva et al. (2014)	The study from two universities (private/public)	U.S	First-year college students	Roommates	NE	Positive
Larson et al. (2013)	EAT 2010	U.S. (Minnesota)	Adolescents	Self-nominated friends	OLS/MR	Positive
Yang and Huang (2013)	Add Health	U.S.	Adolescents	Self-nominated friends	FE	Positive
Asirvatham et al. (2013a)	Arkansas Center for Health Improvement	U.S. (Arkansas)	Children	Students within the same grade	OLS/FE/RE	Positive
Asirvatham et al. (2013b)	Arkansas Center for Health Improvement	U.S. (Arkansas)	Children	Students within the same grade	OLS/FE/RE	Positive
de la Haye et al. (2011)	A public high-school survey in a major Australian city	Australia	Adolescents (12.3-15.6 yrs)	Self-nominated best friends	SAOMs	No effects
Leatherdale and Papadakis (2011)	SHAPES	Canada	Adolescents	Senior students (grades 11 and 12) within the same	Logistic	Positive

				school		
Mora and Gil (2013)	A secondary-school student survey, Catalonia	Spain	Adolescents (14-18 yrs)	Self-nominated friends within the same classroom	OLS/GMM/LIML	Positive
Loh and Li (2013)	CHNS	Rural China	Adolescents (10-19 yrs)	Children in the same age group, level of school and community; Children in the same age group and community	OLS/2SLS/QR	Positive

Note: Add Health = the National Longitudinal Study of Adolescent Health; EAT = the Eating and Activity in Teens in 2010; and SHAPES = the School Health Action, Planning, and Evaluation System. The estimation methods are as follows: Logistic=logistic model; LLM=longitudinal logistic-regression model; Ologit=ordered logit model; Probit= probit model; TSLS= two stage least squared model; IV-Probit= instrumental variable probit model; RE-Logistic= random effects logistic model; ERGM= exponential random graph model; SAOMs=stochastic actor-oriented models; FE=fixed effects model; RE=random effects model; MCS=Monte Carlo Simulations; QR=quantile regression model; NE=natural experiment method (using random roommate assignments); GMM= general method of moments model; LIML=limited information maximum likelihood model; and MR= mean regression.

As Table 4.1 suggests, we know of only a handful of studies on this topic outside the U.S. Among these, Leatherdale and Papadakis (2011), using cross-sectional data from the Physical Activity Module (PAM) of the School Health Action, Planning, and Evaluation System (SHAPES) in Ontario, Canada, confirm that the likelihood of overweight or obesity for junior students (grades 9 and 10) is significantly influenced by the prevalence of obesity among senior students (grades 11 and 12). Likewise, Mora and Gil (2013), using a sample of secondary school students in Catalonia, Spain, identify a positive and significant casual effect of friend's mean BMI on an adolescent's BMI.[26] An Australian study by

[26] Mora and Gil (2013) use OLS, GMM, and LIML estimations to evaluate the causal relation between adolescent BMI and friend mean BMI. In the GMM and LIML estimates, the IV candidates include

de la Haye et al. (2011), however, based on a four-wave dataset from a public high-school in a major Australian city, finds no correlation between adolescents' BMI and that of their friends.[27] In perhaps the only study outside the Western domain, Loh and Li (2013)[28] draw on data from the 2000 China Health and Nutrition Survey (CHNS), which targets individuals aged 10-19 years living in rural areas, to show that peer effects on adolescents' BMI also exist in the Chinese sample and are particularly strong at or below median BMI and among females.

Given our research aim, it is important to highlight three aspects of past research: First, virtually no research exists on peer effects among children (as opposed to adolescents and adults). To the best of our knowledge, only the unpublished Arkansas study shows that peer effects are significantly correlated with childhood obesity (Asirvatham et al., 2013a; Asirvatham et al., 2013b). Second, research seldom explores the underlying mechanisms of such an effect, even though, as An (2011) emphasizes, knowing how peer effects translate into individual obesity would throw light on the specific pathways through which

mother's education, mean age, and the share of single or divorced parents of the respondents' friends-of-friends who are not friends with the respondent.

[27] De la Haye et al. (2011) apply stochastic actor-oriented models (SAOMs) to a sample of 156 students aged 12.3 to 15.6 years to evaluate the role of adolescents' friend selection and the possible influences of friends' BMI on changes in individual BMI.

[28] On the other hand, numerous studies analyze the effects of peers on other individual outcomes in China. For example, based on the China Health and Nutrition Survey, Li et al. (2013) examine the influence of peers on children's school dropout rate in rural China, suggest that this rate would increase 0.39 to 0.50 percent if peers' dropout rates increased by 1 percent. Ding and Lehrer (2007), in a study of peer influences on the academic outcomes of secondary school students, find strong evidence of the presence of peer effects but in a positive and nonlinear form. Similarly, Carman and Zhang (2012) suggest that peer effects are significantly positive for the math test scores of middle school students but insignificantly positive for Chinese test scores and have no influence on English test scores. Using data from a Chinese college, Han and Li (2009) investigate residential peer effects on higher education and find that only female academic achievements (Grade Point Average, GPA) are responsive to the effects of peers' academic results (College Entrance Test rankings). They find no peer effects on becoming a Communist Party member. Kato and Shu (2009) also provide evidence for the presence of peer effects in the manufacturing workplace in China, showing that workers are more likely to improve performance if they are working with more capable teammates. Another interesting study, conducted by Chen et al. (2008), using the Chinese Household Income Project Survey (CHIP) 2002, presents evidence that peer effects significantly increase individual migration.

peer effects work; for example, the influence of peers on dietary patterns, physical activities, and perceptions of body weight. One possible exception is Blanchflower et al. (2009) analysis of data from the Eurobarometer and the German Socioeconomic Panel (GSOEP), which shows that self-perception of overweight is affected by an individual's BMI relative to a broadly defined peer group. Finally, although nonlinear peer effects seem to exist in other domains, little is known about the potentially nonlinear relation between peer effects and individual obesity.[29] These three points highlight the contributions of our study: not only is it one of the first to focus on children as well as adolescents, it also examines peer effects in a non-Western environment, sheds initial light on the transmission mechanisms through which peer effects may work, and takes a detailed look at possible nonlinear peer effects on obesity.

4.3 Identification of peer effects and analysis of mechanisms

Despite a wealth of studies on peer effects, because of methodological difficulties in specifically identifying the effects themselves, little consensus exists on their importance and magnitude (Manski, 1993). More specifically, an individual's obesity might be associated with that of a peer group because of a causal (or endogenous) effect, contextual (exogenous) effect, correlated effect, or selection effect. The first refers to a direct effect of the peer group on the individual, while the second recognizes that an individual's bodyweight could be influenced by peer group characteristics other than bodyweight. The third

[29] Based on CHIP data, Chen et al. (2008) examine the nonlinear pattern of peer effects on migration decisions in rural China. Ding and Lehrer (2007) uses semiparametric methods to confirm the nonlinearity of peer effects on the academic outcomes of secondary school students in one county of Jiangsu province in China.

acknowledges that both the individual's and the peers' body weight may be influenced by some unobservable factors (e.g., required physical exercise at school), and the fourth accounts for the possibility that obese individuals may select friends that are themselves obese. It is particularly worth noting that if a correlation between individual and peer-group obesity emanates from one of the last three effects, then interventions aimed at reducing obesity are less likely to result in the oft-cited social spillover effect (Trogdon et al., 2008). In this section, therefore, we define our peer-group concept and explain how we intend to identify these different effects. We also outline our approach to identifying the underlying mechanisms.

4.3.1 Definition of peers

Although the literature suggests many different peer group compositions, including respondent-identified friends, classmates, roommates, and neighbors (see Table 4.1 above), it is in essence possible to distinguish between broad (e.g. grade-level) and narrow (e.g. friend-level) peer definitions. Whereas broad definitions capture changes in norms and social attitudes, narrower definitions need not do so and may instead operate through influences on diet and physical activity (Trogdon et al., 2008). In our study, we use a broad peer group; namely, children in a similar age group within a specific community.

4.3.2 Contextual effects/exogenous effects

As pointed out above, an individual's bodyweight may be affected by unobservable characteristics of the peers, such as their family and cultural backgrounds (Yakusheva et al., 2011), which would bias a direct peer effect. We therefore employ a rich set of household, community, and provincial variables to capture diverse characteristics of the peer reference group.

4.3.3 Correlated effects/reflection problem

Correlated effects imply that common environments and institutions might simultaneously affect the bodyweight of both individuals and their peers. It is thus important that any investigation into the relation between peer effects and individual obesity take into account potential confounders (Yakusheva et al., 2011). We do so by including a very rich set of community-level variables, including food prices and the availability of fast food restaurants and recreational facilities (gym/exercise centers, park/public recreation places, playgrounds) in the community. We also include provincial dummies that capture unobservable factors like geographic and climate conditions, which do not vary across time. Such community-level variables control for a common environment at the community level, one shared by both the individuals and their peer groups. We also control for correlated effects stemming from unobservables at the community level using fixed effects models.

4.3.4 Selection effects

Given that individuals can generally choose their friends, roommates, or neighbors, it is sometimes difficult to disentangle peer selection from peer influence, which might lead to an overestimation of peer effects (Fletcher, 2011). In our case, however, because peer groups are defined at the community level, it seems unlikely that peer selection is an issue (as in Trogdon et al., 2008). Furthermore, the Chinese *Hukou* system has in the past considerably inhibited the free choice of residential community (Lu and Wan, 2014), thereby strongly mitigating the selection issue.

4.3.5 Analysis of underlying mechanisms

When the analysis uses a broad peer-group measure like ours, the peer effect may work via its influence on accepted BMI norms or BMI standards for bodyweight in a community (Burke and Heiland, 2007). In this present study, therefore, we also analyze adolescents' perceptions of bodyweight; more specifically, whether self-reported perceptions of weight status – underweight, normal weight, or overweight – is affected by peer BMI. If peer BMI affects norms or standards, then this effect may be captured by individuals' perceptions of their own bodyweight. All else being equal (especially with regards to individual BMI), individuals whose peers have a higher BMI should be less likely to consider themselves overweight. Analyzing such perceptions could provide strong evidence for the existence of peer effects. That is, although it is difficult to ensure that all contextual and correlated effects have been accounted for in an analysis of the relation between peer and individual BMI, such effects are unlikely to be the drivers of any correlation between peer BMI and individual bodyweight perceptions.

4.4 Data and methods

4.4.1 Survey and sample

Our data are taken from the China Health and Nutrition Survey (CHNS), which has been conducted in nine waves (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011).[30] The survey sample is drawn from nine provinces (Liaoning, Heilongjiang[31], Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou) with different social, economic, and health situations. The survey's multistage random cluster sampling method, which is based on different income levels (high, medium, and low) and weighted sampling, entails the following steps: After randomly selecting four counties and two cities within each province, the CHNS randomly identifies villages and towns in each county and urban and suburban regions in each city. It then selects 20 households from each of these communities, which in 1989 and 2009 numbered 190 and 218, respectively (see Popkin et al., 2010, for a detailed description of the CHNS dataset).

In the present study, the data for the empirical analysis include the three waves for 2004, 2006, and 2009, primarily because the information on recreational facilities in the community (such as the availability of playgrounds) has only been available since 2004. After we drop missing values for the control variables, our selected sample comprises 2,186 children and adolescents aged 3-18 years. To identify any potential heterogeneity of peer effects on bodyweight for these subjects, we analyze three age groups separately: 3- to 18-year-olds (all), 3- to 9-year-olds (children), and 10- to 18-year-olds (adolescents).[32] Because of limited availability of data on self-reported perceptions of bodyweight,[33] our pathway analysis is restricted to adolescents aged 10 to 18 years.

Peers

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30 Our analysis goes only through 2009 because the 2011 data for individual weight and height are currently unavailable.

31 Heilongjiang province was introduced as the ninth province in 1997, but Liaoning province did not participate in that year because of natural disasters at the time.

32 Here, the age cutoff of 10 years for children and adolescents is based on a WHO criterion. Specific descriptions are available from http://www.who.int/topics/adolescent_health/en/.

33 In the CHNS, information on self-reported perceptions of bodyweight is available for children aged ≥6 years from wave 2000 onwards.

We broadly define peers as all individuals in the same age band and same community, excluding the target individual i (for a similar definition, see Loh and Li, 2013). We divide the individual age bands into five groups, 3–5, 6–8, 9–11, 12–14, and 15–17 years, and calculate the leave-out average BMI peer effects[34] as follows:

$$\overline{BMI}_{(i)jc} = \left(\sum BMI_{ijc} - BMI_{ijc}\right) / \left(N_{jc} - 1\right)$$

where BMI_{ijc} designates individual i's BMI in age band j and community c. $\overline{BMI}_{(i)jc}$ denotes the average BMI of peers in age band j and community c without individual i, and N_{jc} indicates the sample size of individuals in age band j and community c.

When analyzing individual perceptions, we slightly adjust the age ranges in order to focus on adolescents (i.e., those between 10 and 18). Specifically, we define the age bands as follows: 10–11, 12–13, 14–15, and 16–17 years.

Dependent variables

The dependent variables of interest are individual BMI and self-reported perception of bodyweight. The survey calculates child or adolescent BMI as individual weight (in kilograms) divided by squared height (in meters), all measured and recorded by professional health workers. Self-reported perception of individual weight is based on the following question:

Do you think you are now underweight, normal, or overweight? 0=underweight; 1=normal; 2=overweight; 9=unknown

[34] For an interesting discussion of leave-out and full average peer effects, see Angrist (2013).

We drop any observations of self-reported perception of weight with a value of 9 (unknown).

As a robustness check, we also employ BMI *z*-scores based on growth charts from the International Obesity Task Force (IOTF) (Cole et al., 2000), which, being based on a broad set of countries that includes Hong Kong, is more appropriate for evaluating Chinese overweight and obesity than alternative growth charts (see, e.g.,Monasta et al., 2010). As a further robustness check, we also use waist circumference as an alternative anthropometric measure of obesity.

The independent variables are categorized into three groups: individual, family and mother, and community variables.

Individual controls

Our specifications include two individual variables: age and gender. The gender dummy equals 1 if the individual is a male, 0 otherwise.

Family and mother controls

Five variables make up the controls for family and mother: mother's BMI, mother's education level, mother's employment status, household per capita income (i.e., total household income divided by household size) adjusted to 2011, and household size. Mother's BMI is mother's weight (in kilograms) divided by squared height (in meters), and mother's education level is measured by years of schooling. The dummy for mother's employment status equals 1 if the mother is currently working, 0 otherwise.

Community controls

The community controls are divided into four subgroups measured by dummy variables: public schools, fast food restaurants, recreational facilities, and real food prices in the community. Dummy variables for public schools (primary school, lower middle school, and upper middle school) in the community equal 1 if this type of school is present in the community, 0 otherwise. The dummy variable for fast food restaurants is equal to 1 if a fast food restaurant is available nearby, 0 otherwise. Dummy variables for public recreational facilities – including gym/exercise centers, park/public recreation places, and playgrounds – all equal 1 if such recreation facilities are accessible in the community, 0 otherwise. We also control for 20 different food prices[35] (yuan/kilograms, adjusted to 2011) in the free markets near the community, including rice, bleached flour, unbleached flour, corn flour, millet, sorghum, rapeseed oil, soybean oil, peanut oil, sugar, eggs, commonly eaten vegetables, pork, chicken, beef, mutton, fresh milk, milk powder, fish, and beancurd.

4.4.2 Estimation strategies

We begin with an OLS model of the following form:

$$BMI_{ijc} = \beta_0 + \beta_1\overline{BMI}_{(i)jc} + \beta_2 X_{ic} + \beta_3 F_{ic} + \beta_4 Z_c + \beta_5 W_c + \beta_6 P_c + \varepsilon_{ic} \quad (1)$$

where X_{ic} is a vector of individual i's characteristics, F_{ic} is a vector of family and mother characteristics, Z_c is a vector of community characteristics, and W_c is a vector of the year dummy (with 2004 as the reference year). P_c is a vector of the

[35] It is worth noting that there are three major sources of price information in CHNS: free market prices, state-owned store prices, and authorities' price records (Guo et al., 2000). Since 1989, however, state-owned stores have been gradually replaced by free markets and supermarkets, and most food is currently accessible on the free market (Du et al., 2004). We thus employ free market prices (adjusted to 2011).

province dummy (with Liaoning as the reference province), ε_{ic} is the individual-specific error term, and β_1 is the coefficient representing the effect of peers on child/adolescent BMI. The correlated effects are captured mainly by the coefficient β_4, which represents the impact of shared community environments on both individual weight and peer effects.

To examine whether the mean peer BMI has a different impact on different points of the individual BMI distribution conditional on the covariates, we use quantile regressions estimated at the 25th, 50th, and 75th percentiles using the same specifications as in the OLS model. We also investigate whether the mean peer BMI influences adolescents' self-reported perception of bodyweight by applying an ordered probit model to these same specifications.

Although we control for numerous community-level covariates associated with individual bodyweight, there may still be some unobservables present in the community or province. Hence, we also employ fixed effects models to control for any unobservable time-invariant heterogeneity related to individual bodyweight. Specifically, we construct pairs of observations for individuals surveyed in two years, pool these pairs (group 1: 2004 and 2006; group 2: 2004 and 2009; and group 3: 2006 and 2009), and then run fixed effects estimations using two group dummy variables (with group 3 as the reference group). We can remove individual time-invariant effects through first differencing. The model to be estimated is thus

$$BMI_{ijc} = \theta_0 + \theta_1 \overline{BMI}_{(i)jc} + \theta_2 X_{ic} + \theta_3 F_{ic} + \theta_4 S_c + \theta_5 G_t + \alpha_i + \varepsilon_{ict} \quad (2)$$

where S_c is food prices on the free market, G_t is a vector of group dummy variables, α_i is the individual time-invariant fixed effect, and ε_{ict} is the idiosyncratic error term.

4.5 Results

4.5.1 Descriptive statistics

As appendix Table A4.1 shows, the mean BMI of children and adolescents aged 3–18 years is 16.61, the average BMI *z*-score is -0.15, and the average peer BMI on the community level equals 16.61. The average BMI of males and females in 2004 was 16.32 and 16.28, respectively, but by 2009, these levels had increased for both males and females to16.75 and 16.77, respectively. As regards self-reported perceptions of weight status, 11.34% of those sampled perceive themselves as overweight, as do 11.43% of the females and 11.27% of the males.

4.5.2 Peer effect estimates

Results for the entire sample and all subsamples (urban/rural, males/females, and children/adolescents) are reported in Table 4.2. The results in column 1, with only the mean peer BMI controlled for, indicate that the average peer BMI significantly and positively correlates with individual BMI (a coefficient equal to 0.596). In column 2, when we introduce individual, mother, and household controls, the peer effect remains significant and positive but with a substantially decreased magnitude (a coefficient equal to 0.369). In column 3, with the addition of year and provincial dummies, as well as community characteristics, the peer coefficient remains significant but the magnitude declines even more (a coefficient equal to 0.281).

Columns 4–7 report the results for the subsamples: the urban and rural estimates indicate that peer effects are positively associated with individual BMI, yet the effect is somewhat stronger in rural than in urban areas (0.283 versus 0.131). This finding may reflect the fact that in China, social ties and norms are stronger in rural communities than in urban areas (Peng, 2004).[36] The middle and bottom of Table II report the estimates for the 3–9 (children) and 10–18 (adolescents) age groups, respectively. A comparison of the estimates in column 3 reveals that the peer effect is not as pronounced among children compared with adolescents.[37] As in other studies (see, e.g.,Trogdon et al., 2008), our estimates based on gender (see columns 6 and 7) show that peer effects are substantially stronger among females than males, especially among adolescents.[38]

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36 Results for other variables included in the regressions but not reported indicate that respondent age is consistently and significantly positively related to individual BMI. Individuals with higher mothers' BMI are more likely to have a higher BMI. Interestingly, those whose mothers have a higher education level also tend to have a higher BMI level. We also ran the regressions controlling for the average age of peers and find that results are quantitatively similar to our results in Table 4.2.

37 The study of Maximova et al. (2008) suggests that children and adolescents who are exposed to overweight parents and schoolmates are prone to underreport their bodyweight, and that younger children aged 9 are notoriously sensitive to the exposure to overweight/obesity both at home and in school.

38 In order to identify a causal relationship between peer effects and individual BMI, we also perform a two-stage GMM procedure. Following Trogdon et al. (2008) and Loh and Li (2013), we adopt average peers' parental BMI as instruments and our results indicate that average peer effects are positive (0.355) and significant at the 5% level. We do, however, observe heteroskedasticity (Breusch-Pagan test=84.81, p-value=0.00). The results are not reported here, but are available upon request. As emphasized by Halliday and Kwak (2009), such an instrumental approach based on background information of peers might be problematic primarily because it comes at the high expense of increased measurement error and weaker instruments.

Table 4.2 OLS estimates of peer effects on individual BMI (3- to 18-year-olds)

	(1) All	(2) All	(3) All	(4) Urban	(5) Rural	(6) Male	(7) Female
Average peer BMI	0.596*** (0.033)	0.369*** (0.039)	0.281*** (0.042)	0.131* (0.079)	0.283*** (0.051)	0.166*** (0.052)	0.392*** (0.065)
CI	[0.532,0.659]	[0.293,0.445]	[0.199,0.364]	[-0.024,0.286]	[0.184,0.383]	[0.064,0.269]	[0.264,0.520]
N	2186	2186	2186	528	1658	1191	995
Adj.R^2	0.168	0.241	0.246	0.240	0.240	0.266	0.237
Children: 3-9-year olds							
Average peer BMI	0.443*** (0.055)	0.367*** (0.056)	0.266*** (0.063)	0.097 (0.147)	0.259*** (0.073)	0.153** (0.077)	0.390*** (0.100)
CI	[0.335,0.551]	[0.257,0.476]	[0.142,0.389]	[-0.192,0.385]	[0.115,0.403]	[0.002,0.304]	[0.193,0.587]
N	1237	1237	1237	303	934	685	552
Adj.R^2	0.080	0.128	0.136	0.158	0.127	0.128	0.149
Adolescents: 10-18-year olds							
Average peer BMI	0.521*** (0.047)	0.275*** (0.056)	0.132** (0.061)	-0.245* (0.139)	0.138* (0.073)	0.039 (0.087)	0.214** (0.086)
CI	[0.429,0.613]	[0.164,0.385]	[0.013,0.251]	[-0.519,0.028]	[-0.005,0.281]	[-0.132,0.210]	[0.044,0.383]
N	949	949	949	225	724	506	443
Adj.R^2	0.125	0.213	0.226	0.150	0.239	0.239	0.240

Note: (1) just includes average BMI of peers, (2) includes individual characteristics (age and gender), mother characteristics (mother BMI, education and employment status), and household characteristics (translog household income measured in yuan, household size) and also urban dummies. (3) includes controls as (2) but adding dummies of years (2004 as the base year) and provinces (Liaoning as the base province), dummies of public schools, dummy of fast food restaurants and recreational facilities in the community, 20 different food prices (yuan/kilograms, inflated to 2011) in the free market. (6) and (7) are controlled without gender dummy. CI means 95% confidence intervals. Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

To check the heterogeneous response of peer effects on different points of the BMI distribution, we also estimate quantile regressions. As Table 4.3 shows, average peer BMI is significantly positive in both the children and adolescent samples on all points of the BMI distribution. Individuals in the upper part of the distribution (75th percentile), however, are more sensitive to average peer BMI than those at the 25th percentile (0.399 versus 0.207).[39] Interestingly, the peer effects for females at the upper end of the distribution are stronger than those for males.

[39] We also ran unconditional quantile regressions and obtained quite similar results as in Table 4.3.

Table 4.3 Quantile regressions of peer effects on individual BMI (3- to 18-year-olds)

All	25%	50%	75%
Average peer BMI	0.207***	0.308***	0.399***
	(0.037)	(0.045)	(0.065)
CI	[0.134,0.281]	[0.218,0.397]	[0.271,0.527]
N	2186	2186	2186
Pseudo R^2	0.138	0.177	0.204
Males	25%	50%	75%
Average peer BMI	0.246***	0.301***	0.325***
	(0.052)	(0.060)	(0.097)
CI	[0.145,0.348]	[0.184,0.418]	[0.135,0.515]
N	1191	1191	1191
Pseudo R^2	0.155	0.188	0.219
Females	25%	50%	75%
Average peer BMI	0.245***	0.299***	0.433***
	(0.060)	(0.075)	(0.096)
CI	[0.126,0.363]	[0.152,0.447]	[0.245,0.622]
N	995	995	995
Pseudo R^2	0.147	0.195	0.212

Note: Models include individual characteristics (age and gender), mother characteristics (mother BMI, education and employment status), and household characteristics (translog household income measured in yuan, household size), urban dummies, dummies of years (2004 as the base year) and provinces (Liaoning as the base province), dummies of public schools, dummy of fast food restaurants and recreational facilities in the community, 20 different food prices (yuan/kilograms, inflated to 2011) in the free market. Split estimates are without gender dummies. CI means 95% confidence intervals. Bootstrapped standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

In Table 4.4, we also estimate peer effects separately for children and adolescents. As the first panel shows, peer effects are significantly positive across the entire BMI distribution. However, girls in the upper part of the BMI distribution are particularly affected by peers (0.577), with a peer effect for females at the 75th percentile over three times larger than that at the 25th percentile.

Table 4.4 Quantile regressions of peer effects on childhood BMI (3- to 9-year-olds)

All	25%	50%	75%
Average peer BMI	0.160***	0.214***	0.321***
	(0.042)	(0.052)	(0.103)
CI	[0.078,0.242]	[0.111,0.316]	[0.118,0.523]
N	1237	1237	1237
Pseudo R^2	0.100	0.115	0.139
Males	25%	50%	75%
Average peer BMI	0.155**	0.244***	0.162
	(0.064)	(0.079)	(0.112)
CI	[0.029,0.281]	[0.089,0.398]	[-0.058,0.383]
N	685	685	685
Pseudo R^2	0.128	0.125	0.149
Females	25%	50%	75%
Average peer BMI	0.182**	0.205**	0.577***
	(0.091)	(0.103)	(0.165)
CI	[0.002,0.362]	[0.002,0.409]	[0.253,0.901]
N	552	552	552
Pseudo R^2	0.104	0.135	0.177

Note: The estimated samples are restricted to the age group 3-9 years. Controls include individual characteristics (age and gender), mother characteristics (mother BMI, education and employment status), and household characteristics (translog household income measured in yuan, household size), urban dummies, dummies of years (2004 as the base year) and provinces (Liaoning as the base province), dummies of public schools, dummy of fast food restaurants and recreational facilities in the community, 20 different food prices (yuan/kilograms, inflated to 2011) in the free market. Split estimates are without gender dummies. CI means 95% confidence intervals. Bootstrapped standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

With regard to adolescents aged 10–18 (see Table 4.5), only adolescents at the upper end of the distribution have a significant positive effect, a marked contrast from the quantile results for children and the general finding that peer effects among children are larger.

Table 4.5 Quantile regressions of peer effects on adolescent BMI (10- to 18-year-olds)

All	25%	50%	75%
Average peer BMI	0.086	0.103	0.240**
	(0.061)	(0.076)	(0.096)
CI	[-0.034,0.207]	[-0.047,0.253]	[0.051,0.429]
N	949	949	949
Pseudo R^2	0.162	0.189	0.205
Males	25%	50%	75%
Average peer BMI	0.013	0.079	0.217
	(0.094)	(0.109)	(0.152)
CI	[-0.171,0.198]	[-0.134,0.293]	[-0.081,0.515]
N	506	506	506
Pseudo R^2	0.195	0.220	0.245
Females	25%	50%	75%
Average peer BMI	0.128	0.106	0.219
	(0.112)	(0.110)	(0.138)
CI	[-0.092,0.348]	[-0.111,0.323]	[-0.053,0.490]
N	443	443	443
Pseudo R^2	0.206	0.229	0.234

Note: The estimated samples are restricted to age groups of 10-18 years old. Controls include individual characteristics (age and gender), mother characteristics (mother BMI, education and employment status), and household characteristics (translog household income measured in yuan, household size), urban dummies, dummies of years (2004 as the base year) and provinces (Liaoning as the base province), dummies of public schools, dummy of fast food restaurants and recreational facilities in the community, 20 different food prices (yuan/kilograms, inflated to 2011) in the free market. Split estimates are without gender dummies. CI means 95% confidence intervals. Bootstrapped standard errors are in parentheses; $^{*}p<$ 0.1, $^{**}p<$ 0.05, $^{***}p<$ 0.01.

Because some unobserved or omitted factors may still exist, we also estimate a fixed effects model. As Table 4.6 shows, although the average peer BMI is still significantly and positively correlated with individual BMI, the coefficient is substantially smaller than in the OLS model (0.17 vs. 0.28). This result is similar to that observed in Asirvatham et al. (2013b), confirming the importance of controlling for unobserved time-invariant fixed effects. Interestingly, the coefficient of a random effects estimate is 0.27, which is quite similar to that of the OLS estimate.

Table 4.6 Fixed-effects estimates of peer effects on individual BMI (3- to 18-year-olds)

Variables	FE	RE
Average peer BMI	0.169***	0.270***
	(0.046)	(0.036)
CI	[0.078,0.259]	[0.200,0.340]
Control for food prices	Yes	Yes
Observations	1772	1772
R^2	0.214	-

Note: The dependent variable is individual BMI. All samples are restricted to the 2004, 2006, and 2009 waves. Model (1) is a fixed-effects estimate with group dummies (group 1=2004 and 2006, group 2=2004 and 2009, and group 3=2006 and 2009, with group 3 as the reference group). CI =95% confidence intervals; standard errors are in parentheses; $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

4.5.3 Operation of peer effects

To explore the pathways through which peer effects may operate, we use an ordered probit to analyze adolescent's self-reported weight perceptions (see Table 4.7). Despite expectations that once individual BMI and other variables are controlled for, a larger average peer BMI might reduce the probability of considering oneself overweight, this result is only significant at the 10% level and only for females.[40] This observation may imply that norms of bodyweight for females do in fact change with peers' BMI levels.[41]

[40] Xie et al. (2003) indicates that female adolescents are more likely to report being overweight. Furthermore, relatively higher perceived peer isolation (defined on a 4-point scale, whether respondents have experienced being looked down or insulted or attacked or isolated by classmates) can be identified among female adolescents who reported being overweight compared with underweight and normal weight.

[41] We also followed Blanchflower et al. (2009) by introducing a measure of relative BMI into the specification. The results, available upon request, are qualitatively very similar.

Table 4.7 Marginal effects of ordered probit estimates of peer effects on adolescents' self-reported weight status (10-to 18-year-olds)

Variables	All	Males	Females
Self-reported underweight	0.004	-0.011	0.017*
	(0.007)	(0.010)	(0.009)
CI	[-0.009,0.017]	[-0.030,0.009]	[-0.0001,0.034]
Self-reported normal weight	-0.001	0.005	-0.006
	(0.003)	(0.005)	(0.004)
CI	[-0.006,0.004]	[-0.004,0.014]	[-0.015,0.002]
Self-reported overweight	-0.002	0.006	-0.011*
	(0.004)	(0.005)	(0.006)
CI	[-0.010,0.001]	[-0.005,0.016]	[-0.022,0.0004]
N	776	426	350
Pseudo R^2	0.157	0.204	0.226

Note: Controls include individual characteristics (age and gender), mother characteristics (mother BMI, education and employment status), and household characteristics (translog household income measured in yuan, household size), urban dummies, dummies of years (2004 as the base year) and provinces (Liaoning as the base province), dummies of public schools, dummy of fast food restaurants and recreational facilities in the community, 20 different food prices (yuan/kilograms, inflated to 2011) in the free market. Split estimates are without gender dummies. CI means 95% confidence intervals. Standard errors are in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We also recoded the self-reported perceptions of weight into a binary variable (1=overweight, 0=normal or underweight) and then estimated a probit model. As Baum (2006) emphasizes, it is particularly useful to examine the distribution of the marginal effects based on each individual in the sample. We thus report the marginal effects for different ages and separately for males and females (see Figure A4.1–A4.3 in Appendix). According to these calculations, in the full sample, the effects are negative and increase with age (see Figure A4.1). Likewise, marginal effects for females are consistently negative and rise with age (see Figure A4.2). In stark contrast, marginal effects for males are uniformly positive but decrease with age. For 10-year-olds, they are less than 0.007 and for 17-year-olds, approximately 0.001 (see Figure A4.3). These results appear to imply that predicted probabilities of self-reported overweight increase as the age of the adolescent increases, particularly for females. Such is not the case for males.

In general, our results are in line with the assumption that peer BMI could influence individual bodyweight perceptions; however, the significance is low. Although this latter could be associated with the low sample size, alternatively it could signal that changes in community-level BMI need not necessarily change perceptions. Rather, they may influence the acceptability of being overweight; that is, even when individuals know they are overweight, the social pressure to lose weight may be lower when community BMI levels are high.

4.5.4 Existence of nonlinear peer effects: parametric estimates

Next, to determine whether community peer effects exert a nonlinear effect on individual BMI for children versus adolescents, we introduce parametric estimates of peer BMI using a squared term of average peer BMI. The OLS estimates (see Table 4.8) reveal that the average peer BMI (positive) and its squared term (negative) are significant for the full sample and adolescents, but not for children. Specifically, they suggest a possible concave relation between peer effects and individual body weight for the full sample and adolescents, which levels out at relatively high BMI levels (around 24 and 20, respectively).

Table 4.8 Parametric estimates of nonlinear peer effects on individual BMI (3- to 18-year-olds)

Variables	Full sample (3-18 year)	Children (3-9 years)	Adolescents (10-18 years)
Average peer BMI	1.057**	0.531	1.813**
	(0.432)	(0.682)	(0.709)
CI	[0.210,1.904]	[-0.806,1.868]	[0.422,3.204]
Average peer BMI squared	-0.022*	-0.008	-0.046**
	(0.012)	(0.020)	(0.020)
CI	[-0.046,0.002]	[-0.048,0.032]	[-0.085,-0.007]

N	2186	1237	949
Adj.R^2	0.247	0.135	0.231

Note: The dependent variable is individual BMI. Controls include individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy, year dummies (with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). CI =95% confidence intervals, shown in brackets; robust standard errors are in parentheses;$^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

Following Trogdon et al. (2008), we also estimate a double-log model, with the coefficient of average peer BMI now representing elasticity. Like the results in Table 4.1, the elasticities are consistently positive and significant. Once individual, household, and community factors are controlled for, the elasticity of peer effects is 0.281 (see Table A4.2, column 3). The quantile results also indicate that the elasticities of peer effects increase as the percentiles of individual BMI rise (25th=0.23, 50th=0.31, and 75th=0.36, see Table A4.3, panel 1).[42]

Robustness check using another peer group

Following Loh and Li (2013), we employ an additional peer reference group that might capture information on peer networks at the school level; namely, those in the same age band but also at the same school and community level.[43] We find a significant correlation between peer effects and individual bodyweight except for males (positive but insignificant, see Table A4.4), with the magnitude of peer influence for females being much stronger than that for males. Quantile

[42] To identify whether peer effects have a nonlinear effect, we also estimated a semiparametric partially linear model (PLM), using Robinson's (1988) double residual method. The results are graphed in Figure A4.4 in the appendix. In general, we note a positive linear relation between peer BMI levels and individual BMI for average peer BMI levels ranging between 14 and 19. To further assess whether the nonparametric functions of peer effects might be approximated by some parametric polynomial form, we employ Hardle and Mammen's (1993) specification test. Based on the PLM model, the results (available upon request) indicate that the null hypothesis (i.e.,a parametric polynomial of degree 1) cannot be rejected, suggesting that the relation between individual BMI and average peer BMI is indeed linear.

[43] Our sample size is restricted to respondents aged 6 to 18. Specifically, the school age bands are 6–8, 9–11, 12–14, and 15–17 years. As mentioned previously, we also use a leave-out average peer definition.

regressions, run as an additional step, demonstrate that peer effects are again more evident for those in the upper distribution of individual BMI (25th=0.12, 50th=0.26, and 75th=0.33, see Table A4.5).

Robustness check for strength of same-gender peer effects

To follow up on the discussion in Christakis and Fowler (2007), we also examine whether same-gender peers have a relatively greater influence on individual bodyweight.[44] We find that same-gender peer effects are not stronger than mixed-gender peer effects in all prior results except for the full sample of individuals aged 3–18 and children aged 3–9 (see Tables 4.2 and A4.6). Additional results based on quantile regressions, however, lend scant support for the effects of same-gender peers on individual bodyweight being stronger than those of mixed-gender peers except for individuals aged 3–18 at the 50th percentile (see Tables 4.3 and A4.7). On the other hand, females at the 75th percentile, in contrast to males, are more responsive to same-gender peer effects.

Robustness check comparing results with BMI z*-score*

To check the robustness of the results, we use BMI *z*-scores based on the IOTF growth charts. The corresponding OLS estimates show that peer effects are present and the magnitudes are quantitatively similar to previous estimates using individual BMI (except for the urban group, see Table A4.8). Quantile regressions also confirm that peer effects are much stronger at the upper end of the BMI distribution, particularly among females (see Table A4.9).

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[44] Not only do several U.S. studies suggest that adolescents are more sensitive to the bodyweight of same-gender peers (see,e.g., Renna et al., 2008), but Loh and Li (2013) also find that same-gender peer effects for female adolescents are stronger than those for male adolescents in rural China.

Robustness check using waist circumference

The use of BMI as a proxy for body fat has come under criticism lately because of its inability to distinguish fat from muscle, bone, and other lean body mass (Burkhauser and Cawley, 2008; Gallagher et al., 1996; McCarthy, 2006; Romero-Corral et al., 2008; Wellens et al., 1996; Yusuf et al., 2005). We therefore also estimate our models replacing BMI with waist circumference, which is arguably the most reliable field method for measuring abdominal visceral fat (Snijder et al., 2003). In these results, reported in Tables A4.10 and A4.11, the following points are worth noting: although the peer effect is identifiable using this measure, in our sample, the significance levels are substantially lower, especially for children. These findings are in line with those of Burkhauser and Cawley (2008), who show that different measures of obesity correlate differently with certain social science outcomes. Hence, an interesting avenue for future research would be to assess peer effects using different obesity measures. [45]

4.6 Conclusions

This analysis of obesity-related peer effects outside the Western world, which uses CHNS data to analyze obesity-related peer effects among aged 3- to 18-year-old Chinese, documents the following important observations: First, peer effects do indeed exist, not only among adolescents but also younger children. This finding highlights the importance of peers forming health lifestyles – including diets – at a young age. Second, the magnitude of the peer effects varies

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[45] Following Mora and Gil (2013), we conducted a falsification test that replaces BMI with height, which is unlikely to be affected by peers. The results show that average peers' BMI has no impacts on individual height.

substantially along the individual BMI distribution, being stronger at the upper end than at the bottom or median, which suggests that individuals with a higher BMI are more likely to be affected by peer influence. Third, and in line with U.S. studies on adolescents (e.g.Trogdon et al., 2008), females are generally more affected than males. Peer effects are also substantially larger in rural than in urban areas. Finally, our test of the hypothesis that broad community-level peer measures (possibly via changing societal norms) are related to adolescent's self-perceived bodyweight provides evidence that a higher average peer group BMI is negatively correlated with the probability of a self-perception of overweight, especially for adolescent girls.

Some caveats should be mentioned: First, the surveyed sample of the CHNS is not a representative for China. However, those selected provinces are regionally representative. Second, we cannot rule out correlated effects even though controlling for a wealth of household and community characteristics. This could lead to an upward bias. Our analysis on the pathways through which peer effects operate cannot either claim to be causal, yet is supportive of the notion that peers may influence perceptions.

Overall, therefore, our results not only support the notion that peer effects exist among children and adolescents in both urban and rural China but that their magnitude (OLS: 0.13 and FE: 0.17) falls within the general range found for adolescents in the U.S.[46] (0.16 to 0.30) using specifications similar to ours. Hence, living in a collectivistic society like China's does not, prima facie, appear

[46] Renna et al. (2008), using OLS estimates, show the magnitudes of peer effects to be around 0.164 and 0.165 for males and females, respectively. They do not, however, report their results for the full sample. Trogdon et al. (2008), however, also using OLS estimates, identify a peer effect magnitude of 0.30 for the full sample, while Halliday and Kwak (2009), using fixed effects, estimate it at 0.19.

to make a large difference in the magnitude of peer effects. Evaluating to what extent such a conclusion is generalizable, however, would require much more research across the globe.

Chapter 5 Long Work Hours and Health in China

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Abstract

Using several waves of the China Health and Nutrition Survey (CHNS), this study analyzes the effect of long work hours on health and lifestyles in a sample of 18- to 65-year-old Chinese workers. Although working long hours does significantly increase the probabilities of high blood pressure and poorer reported health, the effects are small. Also small are the negative effects of long work hours on sleep time, fat intake, and the probabilities of sports participation or watching TV. We find no positive association between work time and different measures of obesity and no evidence of any association with calorie intake, food preparation and cooking time, or the sedentary activities of reading, writing, or drawing. In general, after controlling for a rich set of covariates and unobserved individual heterogeneity, we find little evidence that long work hours affect either the health or lifestyles of Chinese workers.

JEL Classification Codes: I10, I12, J22, J81

Keywords: Long work hours; health; lifestyle; China

5.1 Introduction

China's long weekly work hours, among the longest in the world, have given rise to substantial concerns about the negative effects such a work week may have on workers' health (Mishra and Smyth, 2013). In a recent survey of Chinese workers, for example, respondents pointed to long work hours as one of three major reasons for health problems (Tang, 2013). Some therefore argue that the unprecedented economic growth in China may have taken place on the back of employees working long hours (Smyth et al., 2013). As stated by Kingston (cited in Oster, 2014) due to the Confucian belief in total dedication, Chinese employers are prone to overburden their employees. At the same time, the Chinese phenomenon of "*Guolaosi*" (death by overwork) has received widespread attention in the Chinese media.[47] For instance, a report in the prominent nationwide *China Youth Daily* claims that approximately 600,000 Chinese people die annually from working too hard (Monet, 2014).

There is in fact solid evidence that long work hours can be detrimental to health. For instance, according to Bannai and Tamakoshi (2014), although those who work long hours need more time to recover, a long work week restricts the amount of private time available for recovery, which can lead to exhaustion. Less private time may also give rise to irregular lifestyles and unhealthy behaviors, including lack of sleep, unhealthy diets, smoking, and alcohol consumption. Nevertheless, despite a large body of literature in several academic disciplines on the effects of long work hours on health outcomes, it remains difficult to draw

[47] In Japan, this phenomenon is known as "Karoshi".

clear conclusions. As several reviewers emphasize (Bannai and Tamakoshi, 2014), results are mixed and evidence on the impact of long work hours on health remains inconclusive, not only because both “long work hours” and health outcomes are variously defined but because of the heterogeneity of individual characteristics and different uses of covariates. For China especially, the empirical evidence is extremely limited: the only three studies we are aware of (Frijters et al., 2009; Verité, 2004; Zhao, 2008) all use cross-sectional data and analyze only subjective (self-reported) health measures.

The purpose of this study, therefore, is to examine the impact of long work hours on health among Chinese adults aged 18–65 using data from the China Health and Nutrition Survey (CHNS) from 1991 to 2009. Our work thus makes several contributions to the literature: First, it is the most comprehensive analysis for China, where, as mentioned above, the possible negative effect of overwork is an important public health issue. Second, it fills an important research void on a research topic studied predominantly in the West, thereby providing a valuable tool for international comparison. Third, it uses a broad array of health measures, including not only measures of subjective health but also several measures of objective health (e.g., high blood pressure and obesity). Fourth, it explores several possible pathways through which long work hours could affect health. In particular, it assesses the relation between long work hours and specific lifestyles, such as time spent sleeping, preparing meals, and engaging in physical activities. Finally, and contrary to the majority of studies on this topic, it also includes a panel analysis, which allows for controlling unobservable individual heterogeneity.

The general conclusion of our analysis is that long work hours do not seem to have any strong effects on several commonly used subjective or objective measures of health. Nor do our results provide any evidence that long work hours significantly influence diets, physical activity, or sleep time.

The remainder of the paper is structured as follows: Section 5.2 reviews the related literature. Section 5.3 describes our data and methodologies. Section 5.4 reports the results, and Section 5.5 concludes the paper.

5.2 Prior literature

5.2.1 Long work hours and subjective health

One early meta-analysis (Sparks et al., 1997) of 19 studies on work hours and health provides seemingly clear evidence that long work hours have an adverse effect on self-reported health. Nevertheless, the mean correlation between overall health (including physiological and psychological health) and work hours is only 0.130 for physiological health 0.064 and 0.147 for psychological health, suggesting that the association between work hours and self-reported health is far from strong. Another systematic review based on 27 selected psychological and medical studies (van der Hulst, 2003) points out that 13 of these studies on the relation between long (40+ weekly) work hours and health use only subjective health measures, including general health, psychological health, physical health, and fatigue. This review finds a strong positive association between long work hours and physical health (somatic, psychosomatic symptoms, and physical strain) but no association with certain aspects of psychological health, including depression, tension/anger, and suicide. A more recent overview based on 19 studies (Bannai and Tamakoshi, 2014) shows that long work hours (40+weekly or 8+ per day) have a negative association with sleep conditions and also diabetes mellitus (DM) when the latter is proxied by self-reported hypoglycemic medication use. Long work hours are also associated with a higher risk of depression and anxiety symptoms.

Of particular interest to our study is the research on work hours and health in Japan and South Korea, both of which have long work weeks like China (Mishra and Smyth, 2013). For Japan, one examination of how work hours influence the biologic functions of 71 Japanese salesmen aged 22–60 (Iwasaki et al., 1998), for instance, finds little evidence of significant differences between short and long work hours in the probability of self-reported fatigue (a feeling of local physical abnormality). However, another study based on a cross-sectional dataset of 377 Japanese workers (Nishikitani et al., 2005) suggests that overtime has a significant positive correlation with self-rated mental health – as measured by the Hamilton Depression Scale (HDS) and Profile of Mood State (POMS) anger-hostility scores – among both men and women. Nonetheless, once age is adjusted for, overtime work is not significantly associated with self-rated mental health measures. A survey of 843 Japanese male day workers under 60 years, in contrast, indicates that working more than 260 hours per month does have a detrimental effect on subjective depression status (Nagashima et al., 2007).

For Korea, based on a field survey of 238 male engineers aged 22–46 in South Korea, Park et al. (2001a) identify a significant association between weekly work hours and subjective stress response and fatigue complaints before work. Using the same dataset, Park et al. (2001b) find that respondents working more than 60 hours per week are more likely than those working fewer hours to suffer from subjective fatigue complaints. Using the 2006 First Korean Working Conditions Survey, Park et al. (2010) also find that working over 60 hours per week is associated with a pronounced increase in stress, especially for males, in comparison to working less than 40 hours per week.

We know of only three studies that analyze the effect of work hours on subjective health in China.[48] The first, based on a survey of 768 workers at 40 export factories in southern China (Verité, 2004), does associate long work hours with self-reported fatigue, exhaustion, sadness, and depression.[49] Likewise, the second, based on data from the 2008 Urban Migrant Survey covering 3,143 urban migrant workers, shows that working over 60 hours per week has an adverse effect on self-reported mental health (Frijters et al., 2009).[50] A third study by (Zhao, 2008) using 2000 CHNS data, however, assesses all the effects of work hours on self-rated health as insignificant.[51]

5.2.2 Long work hours and objective health

As regards objectively measured health, the review by Sparks, et al. (1997) finds that long work hours have detrimental effects on coronary heart disease (CHD), cardiovascular problems, and stress levels. However, van der Hulst (2003)

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48 In a study on the relation between overtime and psychological well-being among 130 full-time office workers aged 23–44 in a branch of a Chinese information and communication technology company, Houdmont et al. (2011) find that high-level overtime (≥15 hours/week) has lower levels of psychological well-being than low-level overtime (14 hours/week).

49 The 40 factories selected are mainly in the garment, shoe, and knitting industries located in Guangdong, Fujian, Jiangsu, and Zhejiang provinces. The results also indicate, however, that no association exists between long work hours and the risk of occupational accidents (Verité, 2004).

50 The dependent variables are a binary variable for whether or not the individual works at least 60 hours per week and a continuous variable for actual weekly work hours.

51 Zhao (2008) focuses on the determinants of self-reported health status in China, identifying education, region, gender, marital status, and individual body weight as important health factors in China. He also identifies a nonlinear relation between age and health. It should be noted, however, that he provides no clear explanation of how “long work hours” is defined in his study.

documents mixed results: long work hours seemingly have positive effects on cardiovascular disease, diabetes, disability retirement, and fasting blood sugar but negative effects on hypertension, sickness absence, immunity, and noradrenaline (p. 179). Bannai and Tamakoshi (2014) overview, on the other hand, identifies no association between long work hours and blood pressure or type 2 DM.

In Japan of the late 1970s, when Uehata (1978) started to investigate 17 Karoshi cases (i.e., death or permanent disability resulting from cardiac and cerebral infarction caused by overwork), the danger of death due to overwork was brought to light and gained expanding attention as the number of employees faced with long work hours increased substantially during the following decades. Karoshi not only became a serious social problem, but was recognized as an official cause of occupational death for which surviving workers and the families of the victims can claim government compensation (see Iwasaki et al., 2006). In another case study, Uehata (1991) reviewed 203 middle-aged Karoshi victims who had been affected by cardiovascular attacks and for whom such compensation was claimed. Two thirds of these victims under study – mostly male workers – had been exposed to excessive workload including extremely long working hours of more than 60 hours per week, an accumulation of more than 50 hours of overtime in a month, and holiday work previous to the heart attack. The relationship between excessively long work hours and an increased risk of myocardial infarction is confirmed in a case-control study by Liu and Tanaka (2002). In this study, 260 Japanese men aged between 40 and 79 admitted to hospitals due to acute myocardial infarction are matched with respect to age and residence with a control group of 445 men exempt from acute myocardial infarction. The authors show that working excessive overtime, i.e. working more than 60 hours per week doubles the risk of acute myocardiac infarction compared to 40 and less weekly work hours. Moreover, insufficient sleep (less than 5 hours per day or 2 or more days per week with less than 5 hours of sleep) is also associated with a two- to threefold risk of cardiac infarction.

Likewise, Iwasaki et al. (1998) find a significant association between long work hours among salesmen aged 50–60 and a higher risk of systolic blood pressure (SBP), while Hayashi et al. (1996) show that 24-hour average blood pressure is higher among male white-collar employees who work overtime. Similarly, Nakanishi et al. (2001) conclude that long work hours has a negative impact on the risk of hypertension in male white-collar workers aged 35–54. Wada et al. (2006) also confirm that workers with average monthly overtime above 50 hours have lower risks of developing hypertension.[52] For male engineers in South Korea, Park et al. (2001a) report that long work hours increase urinary adrenaline levels and decrease low frequency heart rate variability. A recent study of 322 male patients aged 23–60 in Taiwan (Cheng et al., 2014), however, shows that working 60+ hours per week (versus 40–48 hours), significantly increases the risk for CHD.

5.2.3 Long work hours and individual lifestyles

van der Hulst (2003) summarizes the influence of long work hours on health-related behaviors as follows: in general, they have a weak but positive effect on smoking and unhealthy eating habits, no effect on psychotropic drug use and

[52] Hypertension is defined as SBP≥140 mm Hg or DBP≥90 mm Hg (Wada et al., 2006).

physical exercise, but a negative effect on sleep hours. The effects of long work hours on obesity measures, however, are mixed, showing a positive association with body mass index (BMI) but no association with skinfold thickness. Bannai and Tamakoshi (2014) also find no association between long work hours and such health-related behaviors as alcohol consumption, smoking, weight gain, and physical activity.[53] Nevertheless, a study of 3870 division/section heads and 2666 foremen in Japan (Maruyama and Morimoto, 1996) shows that working over 10 hours per day significantly influences the managers' lifestyle, including sleep patterns and diets. There is also a higher prevalence of smokers and frequent drinkers among the foremen who work long hours.

In terms of health behaviors, a study of male Americans aged 25–55 suggests that longer work hours are negatively correlated with participation in physical activity (Xu, 2013),[54] while a quasi-experiment that exploits the effect of work hours on health and health behaviors in France finds that a decline in work hours is correlated with a decrease in the probability of smoking, alcohol consumption, and also physical inactivity (Berniell, 2012). This latter study solves the work hours endogeneity problem by using a differences-in-differences strategy (DID) and an instrumental variables approach (IV) and thus captures the short-term rather than the long-term effects of work hours.[55]

[53] Based on an sample of 3830 adults age 25-54 from the data of the National Population Health Survey in Canada, Shields (1999) provides interesting evidence that long work hours (41–59 hours per week) have no significant association with physical activity in comparison to standard working hours (35–40 hours per week).

[54] Physical activity is measured with a binary variable equal to 1 if the respondent reported any physical activity or exercises in the previous 30 days (Xu, 2013).

[55] For smoking and BMI, outcome data are available for both the pre- and post-treatment periods, so for these variables, the authors apply a DID approach; for alcohol consumption and physical activity, however, information is only accessible for the post-treatment period, so they adopt an IV method. This study also suggests that there is no association between a reduction in work hours and health status as represented by self-reported health and an index of vital risk (Berniell, 2012).

Overall, a number of aspects of past research are worth emphasizing: First, the empirical results suggest that long work hours negatively affect health measured by some indicators like depressive state, anxiety, coronary heart disease, self-reported physical health and fatigue (see van der Hulst, 2003; Bannai and Tamakoshi, 2014). Second, the association of long work hours with lifestyle is ambiguous except for sleep, for which the findings are quite robust, with an increase in the length of the work week being clearly associated with less sleep time (van der Hulst, 2003). In addition, information on the paths through which long work hours affect health is scant, except for the general causal pathway described by Bannai and Tamakoshi (2014), who outline why long work hours result in health problems. Furthermore, a major drawback in most studies, as van der Hulst (2003) emphasizes, is their cross-sectional design. Studies on associations between long work hours and subjective health are the most common, and only a limited number of studies use both subjective and objective measures of health. Such weakness especially holds for the three studies for China (Frijters et al., 2009; Verité, 2004; Zhao, 2008). In these studies, various subjective health outcomes (self-reported fatigue, exhaustions, sadness, depression, general mental problem and self-reported health) are used and positive associations with work time can be observed – especially with regards to self-reported fatigue, exhaustion, sadness and depression (Verité, 2004) and mental health problems (Frijters et al., 2009). However, no association is found between work time and the increased risk of accidents (Verité, 2004) or self-reported health status (Zhao, 2008). Finally, existing literature on long work hours and health is strongly dominated by research in Western countries and Japan, thereby making generalizations for countries such as China difficult.

To remedy some of these shortcomings, we perform a longitudinal analysis of CHNS data to identify the effects of long work hours on both subjective and objective measures of health among Chinese workers. The CHNS also allows us to investigate possible pathways through which long work hours may influence health.

5.3 Data and methodology

5.3.1 Survey and sample

The China Health and Nutrition Survey (CHNS) currently encompasses 9 waves collected in 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011.[56] The survey is administered to 5884 households, containing 27447 individuals, in 9 Chinese provinces (Liaoning, Heilongjiang,[57] Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou). The multistage random cluster design of this unique large-scale longitudinal dataset successfully captures the substantial spatiotemporal variation in the social, economic, and health dimensions of the Chinese population.

In this study, we use a mostly unbalanced panel for 1991 to 2009. Specifically, we analyze employed individuals aged 18 to 65 and exclude respondents who report working less than 11 hours per week in order to avoid a "healthy worker effect", i.e., we exclude workers who might choose very short work hours because of adverse health conditions like high blood pressure or cardiovascular disease (Yang et al., 2006). After dropping missing values for the control

[56] For further information on the CHNS, see Zhang et al. (2014).
[57] Heilongjiang province was introduced as the ninth province in 1997.

variables, our final sample comprises 11034 Chinese workers aged 18–65 years. Because of the limited availability of data on certain outcome variables, sample sizes vary among the analyzes: specifically, 11034 observations for high blood pressure and obesity based on body mass index (1991-2009), 8793 observations for obesity based on waist circumference (1993-2009), 5300 observations for self-reported health (1997-2006), 4215 observations for daily sleep time (2004-2009), 10933 observations for calorie and fat intakes (1991-2009), 4082 observations for time spend on preparation and cooking (1991-2009), 6822 observations for physical activity (1997-2009), 4055 observations for time spend on watching TV (2004-2009) and 2096 observations for time spend on reading, writing and drawing (2004-2009).

Work hours

Weekly work hours (WH) are measured by the question "how many hours did you work during the past week?" As in Frijters et al. (2009), we integrate WH into the model in two ways: First, we include WH dummy variables by recoding work hours into four categories: 11≤WH≤30, 31≤WH≤40, 41≤WH≤50 and WH≥51. Because 40 hours per week (8 hours per day) is the standard work period dictated by China's Labor Law (Casale and Zhu, 2013), we define long work hours as more than 40 hours per week, a definition also used in several studies cited in the meta-analyses discussed above (see for instance Bannai and Tamakoshi, 2014; van der Hulst, 2003). Furthermore, we select 31–40 work hours per week as our reference category. It is also worth noting that using dummy variables for weekly work hours allow us to capture possible nonlinearities in the long work hours–health relation. Second, we integrate a continuous variable into our models that captures actual hours worked each week.

Subjective health

We use self-reported health (SRH) as the main measure of subjective health. It includes not only mental and physical health but also subjective experience of acute and chronic diseases and overall feelings of well-being (Xie and Mo, 2014). In the CHNS, SRH is measured on a 4-point scale based on the following question:[58] "Right now, how would you describe your health compared to that of other people in your age? 1=bad; 2=fair; 3=good; 4=excellent." These data are only available for 1997 to 2006.

Objective health

As in several past studies, we use obesity and hypertension measures to capture objective measures of health. In the CHNS, blood pressure measurements are taken three times by a health professional using a mercury sphygmomanometer, with a time interval between successive pairs of measures of at least 1 minute

[58] We do not employ other measures of self-rated chronic diseases available in CHNS (i.e., diabetes, myocardial infarction, apoplexy, or asthma) because their prevalence in our sample is very small: 1.27% for diabetes, 0.22% for myocardial infarction, 0.16% for apoplexy, and 0.66% for asthma.

(Lei et al., 2012). We calculate the mean values of systolic blood pressure (SBP) and diastolic blood pressure (DBP) based on the second and third measurements to avoid potential measurement biases.[59] Following most of the existing literature (see for example Lei et al., 2012), we define high blood pressure as a binary variable equal to 1 if the respondent's SBP ≥140 mm Hg or DBP ≥90 mm Hg or the respondent is taking anti-hypertension medication, 0 otherwise.

We assess obesity using both body mass index (BMI) and waist circumference (WC). First, general obesity using BMI is assessed on a scale ranging from 0 to 3, which is based on the following criteria of the Working Group on Obesity in China (WGOC) (Zhou and Cooperative Meta-Analysis Group of the Working Group on Obesity in China, 2002): 0=underweight if BMI<18.5, 1=normal weight if 18.5≤BMI<24, 2=overweight if 24≤BMI<28, and 3= obese if BMI≥28. Central obesity is dichotomized as 1 given a WC ≥85 cm for men and WC ≥80 cm for women, 0 otherwise.

Individual lifestyles

Because individual lifestyles, particularly unhealthy behaviors, may be associated with long work hours (see for example Artazcoz et al., 2009), we analyze three aspects likely to be affected: daily sleep time, diet (calorie and fat

[59] A detailed description of blood pressure measurement is available in Lei et al. (2012).

intake,[60] and time spent on food preparation and cooking), and physical activity (sports and sedentary activities). Individual sleep time per day is measured by the following question: “How many hours each day do you usually sleep, including daytime and nighttime?” Calorie intake is defined as the 3-day average intake in kilocalories, while fat intake is a 3-day mean value in grams. In the CHNS, all respondents are asked directly about all food consumed inside and outside the home, and food items, types of meals, and places of food consumption on the preceding day are recoded (Batis et al., 2014). The time (in hours) spent on food preparation and cooking in the household is assessed as follows: “How much time did you spend per day, on average, cooking and preparing meals?”

For physical activities, we create a dichotomous variable having a value of 1 if the respondent participates in sports, including martial arts, gymnastics, track and field/swimming, ball sports (e.g., soccer, basketball, or tennis), other sports (e.g., ping pong or tai chi), and 0 otherwise. We define sedentary activity as the number of hours per week spent watching TV, reading (e.g., books, newspapers, or magazines), writing, or drawing. Lastly, we categorize the independent variables in our analysis into three subgroups: individual, family, and community characteristics.

[60] Excessive fat intake and insufficient physical activity can result in higher risks for some chronic diseases, including hypertension and diabetes (Ministries of Health and Science and Technology and the National Bureau of Statistics of the Peoples Republic of China, 2004).

Individual characteristics

Individual controls include gender, marital status, education levels, activity levels, health insurance, risky behaviors (smoking, heavy drinking, and obesity), residency area, and work conditions. The gender dummy equals 1 if the respondent is male, 0 otherwise. Marital status is a binary variable equal to 1 for the married, 0 otherwise. Education is measured on a 6-point scale: 0=illiterate, 1=primary school, 2=middle school, 3=high school, 4=technical school, and 5=university or higher. We recode it as dummies with illiterate as the reference group. Activity levels are grouped into five categories: 0=very light, 1=light, 2=moderate, 3=heavy, and 4=very heavy. Individual medical insurance is a dichotomous variable equal to 1 if medical insurance is available for the respondent, 0 otherwise. Residency area is a dummy variable equal to 1 if the respondent lives in an urban area, 0 otherwise.

Working conditions include translog average monthly wage (including subsidies) in the past year and dummy variables for formal employment and types of work unit. Specifically, formal employment is a dummy variable equal to 1 if the respondent works for another person or enterprise as a permanent employee and to 0 if the respondent is self-employed, a temporary worker, or a paid family worker (Chen and Hamori, 2013). Work units are grouped into 8 classes:

0=three-capital enterprise (ownership shared by foreigners, overseas Chinese, and joint venture), 1=government, 2=state service or institute, 3=state-owned enterprise,4=small collective enterprise, 5=large collective enterprise, 6=family contract farming, and 7=private or individual enterprise.

Smoking is classified according to the number of cigarettes smoked per day (NCS): 0=nonsmoker, 1=1≤NCS≤10, 2=11≤NCS≤20, and 3=NCS>20. Heavy drinking is defined by a binary variable equal to 1 if alcohol is consumed three or more times per week, 0 otherwise. Obesity is defined as explained above.

Family characteristics

Family controls include translog household income and household size. We also introduce the availability of safe drinking water, sanitation, and electricity in the household, because they might also affect individual health status. The safe drinking water variable equals 1 if the household's drinking water source is a water plant or ground water more than 5 meters deep, 0 otherwise. The sanitation variable equals 1 if the household can access in-house or outside flushing toilet facilities, 0 otherwise. The electricity variable equals 1 if electric facilities are available for the household, 0 otherwise.

Community characteristics

The presence of health facilities in the community is captured by a dummy variable that equals 1 if a health facility is located in the village/neighborhood and 0 if in another village/town/city or in the respondent's city but in a different neighborhood. The distance to the health facility is a continuous variable measured in kilometers.

5.3.2 Estimation approaches

To examine the cross-sectional association between long work hours and high blood pressure, we use a probit regression model of the following form:

$$HBP_i = \alpha_0 + \alpha_1 WH_i + \alpha_2 I_i + \alpha_3 F + \alpha_4 C + \alpha_5 Y + \alpha_6 P + \varepsilon_i \qquad (1)$$

where HBP_i is a binary variable denoting individual *i*' high blood pressure, and WH_i designates dummies for weekly work hour category or actual weekly work hours of individual *i*. I_i is a vector of individual *i*' characteristics, *F* is a vector of family characteristics, and *C* is a vector of community characteristics. Y is a vector of year dummy variables (with 1991 as the reference year), and P is a vector of provincial dummy variables (with Liaoning as the reference province). ε_i is the error term and α_1 is the key coefficient of interest.

To analyze the impact of long work hours on obesity using waist circumference (measured as a binary variable), we use the same specification as in equation (1).

Likewise, because SRH and BMI-based obesity are both measured on a 4-point scale, we estimate the impact of long work hours on these variables using an ordered probit model, whose specification is also similar to equation (1).

Because of potential biases from individual time-invariant unobservables, we investigate the association between long work hours and high blood pressure by estimating the following fixed-effects logit model:

$$HBP_{it} = \alpha_1 WH_{it} + \alpha_2 G_{it} + \mu_i + \varepsilon_{it} \quad i = 1, \cdots, N; t = 1, \cdots, T \qquad (2)$$

where HBP_{it} denotes individual i's high blood pressure status at time t, and WH_{it} is the work hour category or continuous weekly work hours of individual *i* at time *t*. G_{it} represents a set of time-variant controls including age, translog wage, translog household income, and household size. The individual time-invariant effects are denoted by μ_i, and ε_{it} represents the idiosyncratic error term. Because SRH is ordinal, we employ a fixed-effects ordered logit model of the following form:

$$SRH_{it}^{*} = X_{it}'\beta + \mu_i + \varepsilon_{it}, i = 1, \cdots, N; t = 1, \cdots, T \qquad (3)$$

where SRH_{it}^{*} is a latent variable of self-reported health for individual *i* at time *t*, X_{it} denotes observed characteristics, and μ_i captures the unobserved time-invariant characteristics. The latent variable SRH_{it}^* is related to the observable ordered variable as follows:

$$SRH_{it} = k \ \ if \ \tau_k < SRH_{it}^* \leq \tau_{k+1}, k = 1, \cdots, 4 \qquad (4)$$

For these calculations, we employ a consistent estimator of the fixed-effects ordered logit model, proposed by Baetschmann et al. (2011).[61] In principle, existing estimators (e.g. Chamberlain, 1980; Das and van Soest, 1999; Ferrer-i-Carbonell and Frijters, 2004) simplify the ordered logit model to a binary logit model as the ordered response variable is dichotomized into two categories using a certain cut-off point. The main difference of these estimators is the way the cut-off point for the dichotomization is determined. The Blow-Up and Cluster (BUC) estimator by Baetschmann et al. (2011) estimates all possible dichotomizations jointly and uses observation-specific cut-off points. In a Monte Carlo simulation and in an application of German Socio-Economic Panel (GSOEP) data the authors show that the BUC estimator clearly outperforms the existing estimators, especially those which are based on an endogenous dichotomization where the cut-off points are determined as a function of the outcome variable. Moreover, the BUC estimator is superior if the ordered dependent variable exhibits low

[61] Stata codes for implementing the BUC estimator are available in Baetschmann et al. (2011). This estimator, discussed in detail in Baetschmann et al. (2011), is also used in Bell et al. (2012) in their analysis of working hours constraints and health.

frequencies in certain response categories. For the sake of comparison, we also take self-reported health as a cardinal variable and estimate fixed-effects model of the following form:

$$SRH_{it} = \alpha_1 WH_{it} + \alpha_2 Y_{it} + \mu_i + \varepsilon_{it} \quad i = 1, \cdots, N; t = 1, \cdots, T \qquad (5)$$

where SRH_{it} indicates individual *i*'s self-reported health status at time *t*, and WH_{it} is the work hour category or continuous weekly work hours of individual *i* at time *t*. Y_{it} denotes a set of time-variant controls including age, translog wage, translog household income and household size. The individual time-invariant effects are captured by μ_i, and ε_{it} represents the disturbance error.

To detect the possible impact of long work hours on individual lifestyles, we use an ordinary least square (OLS) estimation as follows:

$$LS_i = \beta_0 + \beta_1 WH_i + \beta_2 I_i + \beta_3 F + \beta_4 C + \beta_5 Y + \beta_6 P + \varepsilon_i \qquad (6)$$

where LS_i is our measure for individual *i*'s lifestyles, including daily sleep time, diet (e.g. calorie and fat intakes, time spend on food preparation and cooking), and sedentary activities (e.g. time spend on watching TV, reading, writing and drawing), and *WH* denotes dummies for weekly work hour category or actual weekly work hours of individual *i*. *I* is a vector of individual *i*'s characteristics, *F* is a vector of family characteristics, and C is a vector of community characteristics. Y is a vector of year dummy variables (with 1991 as the reference year for calorie/fat intakes and time spent cooking and with 2004 as the reference year for sedentary activities), and P is a vector of provincial dummy variables (with Liaoning as the reference province). ε_i is the error term and β_1 is the key coefficient of interest. Additionally, we investigate the impact of long work hours on sports participation (measured as a dichotomous variable) using a probit estimation and adopt the similar specification to equation (6).

5.4 Results

5.4.1 Descriptive statistics

Descriptive statistics are presented in Appendix Table A5.1, which shows that the average age of the workers in our sample is nearly 39, with males accounting for slightly more than half the sample. The average work week is about 47 hours, with around 62% of respondents working more than the national standard of 40 hours per week. Fifteen percent of our sample has high blood pressure, and based on the WGOC criteria, approximately 26.5% are overweight, 6.4%are obese when BMI proxies for general obesity are used, and around 24.3% are obese when WC is used (see Table A5.2 of the Appendix). Additionally, the distribution as well as the trend of weekly work hours from 1991 to 2009 are illustrated in Fig. A5.1 in the Appendix. Two points are worth noting: First, the peak of weekly work hours has shifted significantly to the left, with the modus declining from 48 to 40 hours per week. This is especially the case after 1993, which might be a result of the impact of 1995 Labor Regulations (which reduced weekly work hours from 44 to 40; see Casale and Zhu, 2013). Second, the distribution of weekly work hours has become flatter and dispersion is larger, indicating that the trend observed in Western countries of more heterogeneous work-time arrangements appears to be setting in. We also show the changes of various measures of health from 1991 to 2009 in Table A5.2 of the Appendix.[62] Overall, we observe an increasing trend in the prevalence of high blood pressure and obesity. The average daily sleep time is around 7.89 hours, and the 3-day average calorie and fat intakes are approximately 2393 kcal and 81 grams, respectively.

5.4.2 WH and SRH

As regards the association between long work hours and SRH (see Table 5.1), once confounders are controlled for, relative to a 31–40 hour work week, only working 41–50 hours a week is significantly and negatively associated with SRH (columns 2–4).[63] Interestingly, however, the coefficient for very long work hours

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[62] Regarding Table A2 in the Appendix, although the results are based on WGOC criteria, the prevalence of overweight, general obesity and abdominal obesity are comparable to the results from Xi et al. (2012) based on the criteria from the World Health Organization.

[63] We also note that males have better health than females, which echoes the results observed in Zhao (2008). In addition, household income is an important predictor of good health.

(over 50 per week) is insignificant. The results using actual work hours are also insignificant once control variables are included (columns 6–9). These findings are in line with those of Zhao (2008).

Table 5.1 Ordered probit model estimates for SRH: 1997–2006

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$11 \leq WH \leq 30$	-0.105	-0.098	-0.094	-0.095					
	(0.064)	(0.069)	(0.069)	(0.070)					
$41 \leq WH \leq 50$	0.015	-0.108^{**}	-0.114^{**}	-0.115^{***}					
	(0.041)	(0.044)	(0.044)	(0.045)					
$WH \geq 51$	0.094^{**}	-0.054	-0.053	-0.057					
	(0.038)	(0.047)	(0.047)	(0.047)					
WH					0.003^{**}	-0.001	-0.001	-0.001	0.002
					(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	5300	5300	5300	5300	5300	5300	5300	5300	2233
Pseudo R^2	0.001	0.051	0.053	0.056	0.000	0.051	0.052	0.056	0.069

Note: The dependent variable is self-reported health status measured on a 4-point scale (0=poor, 1=fair, 2=good, 3=excellent); WH = weekly work hours. Specifications (1)–(4) include work hour dummies (with $31 \leq WH \leq 40$ as the reference); (2)–(4) also include individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1997 as the reference); (3) further adds in the characteristics of health facilities in the community and (4) adds in risk behaviors (obesity, smoking, and heavy drinking); (5)–(9) include actual weekly work hours, with (9) regressed only including employees who work 41 hours per week or more. Specification (6) includes the same controls as (2), (7) includes the same controls as (3), and (8) and (9) include the same controls as (4). Robust standard errors are in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

According to the panel analysis results in Table 5.2, relative to working 31–40 hours weekly, working 41–50 hours has a significant but negative impact on SRH irrespective of whether a fixed-effects or fixed-effects ordered logit model is used (see columns 1 and 2). However, when employing the continuous variable, we find no significant association between actual work hours and SRH. Although the results in Table 2 indicate that long work hours do indeed have a negative effect on SRH, as perhaps best shown in column (1), the effect is relatively small (-0.12 on a 4-point scale).

Table 5.2 Fixed-effects estimates of SRH: 1997–2006

	WH dummies		Actual WH		
Variables	(1) Fixed-effects	(2) Fixed-effects ordered logit	(3) Fixed-effects	(4) Fixed-effects ordered logit	(5) Fixed-effects ordered logit
11≤WH≤30	-0.115	-0.250			
	(0.096)	(0.221)			
41≤WH≤50	-0.120**	-0.235*			
	(0.054)	(0.124)			
WH≥51	-0.094	-0.235*			
	(0.064)	(0.132)			
WH			-0.002	-0.006	-0.011
			(0.002)	(0.005)	(0.009)
Observations	3092	6810	3092	6810	1974
R^2	0.019	-	0.015	-	-

Note: The dependent variable is self-reported health status measured on a 4-point scale (1=poor, 2=fair, 3=good, 4=excellent); WH =weekly work hours. Specifications (1) and (2) include work hours dummies (with 31≤WH≤40 as the reference); (3)–(5) include weekly work hours, with (5) regressed only including employees who work 41 hours per week or more. In (1)–(5), the controls are translog wage, age, translog household income, and household size. For (1) and (3), community-level clustered standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

5.4.3 WH and high blood pressure

Table 5.3 shows the probit estimates of the impact of long work hours on high blood pressure. Taking weekly work hours between 31 and 40 as the reference category, we find that working more than 50 hours per week significantly increase the probability of high blood pressure, although the magnitudes are relatively small.[64] This finding is consistent with those of Yang et al. (2006) for a sample of Californian workers. We also calculate the average marginal effects of weekly work hours (from 11 to 70) on high blood pressure, showing that the probability of high blood pressure increases as the weekly work hours increase,

[64] Results for other covariates included in the regressions but not reported here show that respondent age is uniformly and significantly positively correlated with the probability of high blood pressure. Moreover, obesity and overweight are major contributing factors to an increase in this probability.

with marginal effects ranging from 0.134 to 0.162 (see Fig. A5.2 in the Appendix). It is important, however, to highlight that the confidence intervals are relatively wide, suggesting that the uncertainty might be greater. For actual weekly work hours, however (as captured by our continuous variable), we observe no signification association between long work hours and the probability of high blood pressure (see column 9).

Table 5.3 Probit model estimates for high blood pressure: 1991–2009

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
11≤WH≤30	0.083	0.068	0.067	0.056					
	(0.063)	(0.071)	(0.071)	(0.072)					
41≤WH≤50	-0.109***	0.064	0.062	0.072					
	(0.035)	(0.047)	(0.047)	(0.048)					
WH≥51	0.110***	0.142***	0.143***	0.152***					
	(0.039)	(0.050)	(0.050)	(0.051)					
WH					0.002*	0.002	0.002	0.002*	0.0004
					(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	11034	11034	11034	11034	11034	11034	11034	11034	6844
Pseudo R^2	0.004	0.126	0.126	0.164	0.0004	0.125	0.126	0.164	0.175

Note: The dependent variable is a dummy for high blood pressure; WH =weekly work hours. Specifications (1)–(4) include the work hour dummies (with 31≤WH≤40 as the reference); (2)–(4) also include individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1991 as the reference); (3) further includes the characteristics of health facilities in the community, and (4) adds in risk behaviors (obesity, smoking, and heavy drinking). Specifications (5)–(9) include actual weekly work hours, with (9) regressed only including employees who work 41 hours per week or more; (6) includes the same controls as (2), (7) includes the same controls as (3), and (8) and (9) include the same controls as (4). Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

In all the specifications for the fixed-effects logit estimates (which rely on a much smaller sample size), the odds ratios indicate no significant association between long work hours and high blood pressure (see Table 5.4). Individual heterogeneity could thus be driving the significant results in Table 5.3, although the small (and different) samples make drawing such a conclusion difficult.

Table 5.4 Fixed effects logit estimates of high blood pressure: 1991–2009

Variables	(1) WH dummies	(2) Actual WH	(3) Actual WH (≥41)

11≤WH≤30	0.842		
	(0.219)		
41≤WH≤50	0.919		
	(0.140)		
WH≥51	1.272		
	(0.225)		
WH		1.005	1.013
		(0.005)	(0.010)
Observations	1965	1965	887

Note: The dependent variable is a high blood pressure dummy; WH = weekly work hours. Specification (1) includes work hour dummies (with 31≤WH≤40 as the reference); (2) and (3) include actual weekly work hours, with (3) regressed only including employees who work 41 hours per week or more. Controls include translog wage, age, translog household income, and household size. Standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

As a robustness check, we also separately explore the influence of long work hours on systolic blood pressure (SBP) and diastolic blood pressure (DBP). As Appendix Table A5.3 shows, relative to the reference category of 31–40 hours, working over 50 hours per week has a significant and positive impact on both SBP and DBP (see columns 1 and 4). These results not only conform to those in Table 3 but are in line with Iwasaki et al. (1998) finding that the SBP of 50- to 60-year-old Japanese salesmen working long hours is significantly higher than that of colleagues working shorter hours.[65]

[65] To shed light on the association between long work hours and cardiometabolic risks in general (diabetes, dyslipidaemia, hypertension, and inflammation), we analyze biomarker data from the CHNS, which, however, are only available for 2009 and for quite a small sample. Specifically, we create binary variables for prediabetes, diabetes, dyslipidaemia, and inflammation, and then, following and, define the prediabetes dummy as a dichotomous variable equal to 1 if total glucose is ≥100 mg/dL and <126 mg/dL, and 0 otherwise. Likewise, the diabetes dummy equals 1 if total glucose is ≥126 mg/dL, dyslipidaemia equals 1 if total cholesterol is ≥200 mg/dL, and the inflammation dummy equals 1 if the high sensitivity C-reactive protein exceeds 2 mg/dL.The results from the probit estimates indicate that long work hours are not associated with prediabetes, dyslipidaemia, or inflammation. However, relative to working 31–40 hours per week, working 41–50 hours weekly has a significant negative impact on the probability of diabetes. These results are available from the author upon request.

5.4.4 WH and obesity

The association between long work hours and general (BMI-based) or central (WC-based) obesity is depicted in Tables 5.5 and 5.6, respectively.[66] In Table 5.5, which reports ordered probit estimates for BMI-based obesity, although long work hours are significantly and negatively correlated with obesity when no controls are included, significance vanishes once other covariates are introduced (see columns 1 and 2). Likewise, the results for actual weekly work hours (columns 3 and 4) provide no evidence that work hours are associated with obesity. Even when the sample is restricted to individuals working more than 40 hours (column 5), we observe no significant relation.

Table 5.5 Ordered probit estimates for long work hours on BMI-based obesity: 1991–2009

Variables	(1)	(2)	(3)	(4)	(5)
$11 \leq WH \leq 30$	-0.0931^{*}	0.0387			
	(0.049)	(0.053)			
$41 \leq WH \leq 50$	-0.2532^{***}	-0.0166			
	(0.026)	(0.034)			
$WH \geq 51$	-0.1003^{***}	-0.0126			
	(0.029)	(0.036)			
WH			-0.0015	-0.0003	0.0019
			(0.001)	(0.001)	(0.002)
N	11034	11034	11034	11034	6844
$Pseudo R^2$	0.005	0.061	0.0001	0.060	0.067

66 In most models we note that obesity tends to increase with household income. This is particularly pronounced when using WC. Furthermore, those individuals who have a higher education level are less likely to have a higher BMI level.

Note: The dependent variable is an obesity dummy (measured on a 4-point scale ranging from 0 to 3); WH =weekly working hours. Specifications (1) and (2) include dummies for working hours (with 31≤WH≤40 as the reference); (2) also includes individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1991 as the reference); (3)–(5) include actual weekly working hours, with (5) regressed only including employees who work 41 hours per week or more. Specifications (4) and (5) include the same controls as (2). Robust standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

To control for individual time-invariant or omitted factors, we also estimate fixed- effects and fixed-effect ordered logit models. As Table 5.6 shows, obesity is significantly and negatively affected by working either 41–50 hours per week, according to the fixed-effects estimation (column 1), or over 50 hours per week, according to the fixed-effects ordered logit estimation (column 2). When we use our continuous variable for actual work hours, however, the coefficients are negative (see columns 4 and 5).

Table 5.6 Fixed effects estimates for long work hours on BMI-based obesity: 1991–2009

	WH dummies		Actual WH		
Variables	(1) Fixed-effects	(2) Fixed-effects ordered logit	(3) Fixed-effects	(4) Fixed-effects ordered logit	(5) Fixed-effects ordered logit
11≤WH≤30	-0.011	0.002			
	(0.026)	(0.127)			
41≤WH≤50	-0.056***	-0.113			
	(0.018)	(0.073)			
WH≥51	-0.002	-0.303***			
	(0.019)	(0.106)			
WH			-0.0003	-0.008***	-0.008*
			(0.001)	(0.003)	(0.004)
Observations	7576	19269	7576	19269	10757
R^2	0.019	-	0.015	-	-

Note: The dependent variable is BMI measured on a 4-point scale; WH = weekly work hours. Specifications (1) and (2) include work hour dummies (with 31≤WH≤40 as the reference); (3)–(5) include weekly work hours, with (5) regressed only including employees who work 41 hours per week or more. In (1)–(5), the controls are translog wage, age, translog household income, and household size. For (1) and (3), community-level clustered standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

Table 5.7 reports the probit estimates for the link between long work hours and obesity as measured by WC. Although the results in columns 1 and 2 are similar to those for the BMI measure, there is no association between long work hours and central obesity once other factors are controlled for. With regard to actual work hours, the impacts on central obesity are consistently negative, albeit with different significance levels, and no correlation emerges with working over 40 hours per week (see column 5). These findings are consistent with those of Burkhauser and Cawley (2008), who show that different measures of obesity correlate differently with certain outcomes. However, our results do not support a positive association between work time and obesity.

Table 5.7 Probit estimates for long work hours on WC-based obesity: 1991–2009

Variables	(1)	(2)	(3)	(4)	(5)
$11 \leq WH \leq 30$	-0.163***	0.016			
	(0.062)	(0.082)			
$41 \leq WH \leq 50$	-0.297***	-0.014			
	(0.036)	(0.054)			
$WH \geq 51$	-0.148***	-0.066			
	(0.037)	(0.056)			
WH			-0.003***	-0.003*	-0.004
			(0.001)	(0.002)	(0.003)
N	8793	5201	8793	5201	2842
PseudoR^2	0.007	0.115	0.001	0.116	0.131

Note: The dependent variable is a binary WC-based obesity variable; WH = weekly working hours. Specifications (1) and (2) include work hour dummies (with 31≤WH≤40 as the reference); (2) also includes individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1993 as the reference); (3)–(5) include actual weekly work hours, with (5) regressed only including employees who work 41 hours per week or more. Specifications (4) and (5) include the same controls as (2). Robust standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

Corresponding results for WC-based obesity are presented in Table 5.8. The odds ratios indicate no significant association between long work hours and central obesity when using dummies for weekly work hours (see column 1 of Table 5.8). Nevertheless, as for actual work hours, we find that working longer hours per week might decrease the odds of central obesity, although the magnitudes are relatively small (see columns 2 and 3).

Table 5.8 Fixed effects logit estimates of WC-based obesity: 1991-2009

Variables	(1) WH dummies	(2) Actual WH	(3) Actual WH (≥41)
11≤WH≤30	1.187		
	(0.383)		
41≤WH≤50	0.926		
	(0.172)		
WH≥51	0.923		
	(0.194)		
WH		0.993	0.978*
		(0.007)	(0.013)
N	1381	1381	453

Note: The dependent variable is a binary WC-based obesity dummy; WH = weekly work hours. Specification (1) includes work hour dummies (with 31≤WH≤40 as the reference); (2) and (3) include actual weekly work hours, with (3) only including employees who work 41 hours per week or more. Controls include translog wage, age, translog household income, and household size. Standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

Overall, our results provide no strong evidence that long work hours have a major impact on either subjective or objective measures of health. Even when a significant association exists, the size of the effect is small, and in the case of obesity, long work hours actually have a negative effect.

5.4.5 WH and sleep

According to van der Hulst (2003), long work hours may decrease sleep time, which could in turn have negative health consequences. In fact, as Table 5.9 shows, relative to the 31–40 hour work week, working 41–50 and over 50 hours per week is likely to decrease daily sleep time (column 2).[67] This observation is supported by the results for actual weekly work hours, which also indicate a significant negative association between work week length and daily sleep time (columns 3–5). Nonetheless, the magnitudes are small: working over 50 hours reduces sleep time by about 10 more minutes than working 31 to 40 hours per week. These results are in line with those of Park et al. (2001a) for South Korea and Maruyama and Morimoto (1996) for Japan.[68]

Table 5.9 OLS estimates for individual sleep time: 2004–2009

Variables	(1)	(2)	(3)	(4)	(5)
$11 \leq WH \leq 30$	0.087	0.041			
	(0.068)	(0.070)			
$41 \leq WH \leq 50$	-0.049	-0.099^{**}			
	(0.042)	(0.044)			
$WH \geq 51$	-0.111^{***}	-0.209^{***}			

67 Results also indicate that age is consistently and negatively related to daily sleep time. Furthermore, urban respondents are more likely to sleep less in comparison to rural ones.

68 In order to keep the presentation tractable, we only report results of the pooled cross-sectional regressions when analyzing the lifestyle variables. We however also conducted fixed-effects analyzes for all the lifestyle variables and these results are available from the authors upon request. The general conclusions of this paper are not affected by the use of panel techniques, because all the estimated coefficients are either insignificant or correspond to the cross-sectional estimates.

	(0.040)	(0.048)			
WH			-0.005***	-0.007***	-0.007***
			(0.001)	(0.001)	(0.002)
N	4215	4215	4215	4215	2045
Pseudo R^2	0.002	0.034	0.005	0.036	0.033

Note: The sample is restricted to three waves: 2004, 2006, and 2009. The dependent variable is individual sleep time per day; WH = weekly work hours. Specifications (1) and (2) include work hour dummies (with 31≤WH≤40 as the reference); (2) also includes individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 2004 as the reference); (3)–(5) include actual weekly work hours, with (5) regressed only including employees who work 41 hours per week or more. Specifications (4) and (5) include the same controls as (2). Robust standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

5.4.6 WH and diet

Because long work hours might increase unhealthy dietary patterns, we also examine their possible impact on calorie and fat intake. As Table 5.10 shows, however, little evidence emerges for any such association: only in our subsample of those working over 40 hours per week is there a small *negative* correlation between work time and fat intake (see column 6).[69]

Table 5.10 OLS estimates for long work hours on calorie/fat intake (log-log model): 1991–2009

	Calorie intake			Fat intake		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
11≤WH≤30	0.031**			0.028		
	(0.013)			(0.024)		
41≤WH≤50	-0.003			0.023		
	(0.009)			(0.015)		
WH≥51	0.009			0.012		
	(0.009)			(0.016)		
WH		-0.014	-0.005		-0.016	-0.093**
		(0.011)	(0.024)		(0.021)	(0.043)
N	10933	10933	6780	10933	10933	6780
Adj.R^2	0.149	0.149	0.154	0.086	0.086	0.078

Note: The dependent variable is translog individual 3-day averaged calorie intake (in kcal) or fat intake (in grams); WH = weekly work hours. Specifications (1) and (4) include work hour dummies (with 31≤WH≤40 as the reference), as well as individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1991 as the reference); (2), (3), (5) and (6) include weekly work hours, with (3) and (6) regressed only including employees who work 41 hours per week or

69 Results also show that males tend to exhibit higher levels of calorie and fat intakes. Moreover, those with a higher household income level or living in an urban area are more likely to have a higher level of fat intake. A larger household size is related to a decline in individual calorie and fat intake.

more. Specifications (2), (3), (5) and (6) include the same controls as (1). Robust standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.

Likewise, once other covariates are controlled for, no significant association emerges between long work hours and time spent on food preparation and cooking (see Table 5.11).[70] Moreover, the results for actual work hours (even those restricted to ≥41 hours) are similar to those using dummy variables.

Table 5.11 OLS estimates for long work hours on food preparation and cooking time: 1991–2009

Variables	(1)	(2)	(3)	(4)	(5)
11≤WH≤30	-0.0028	0.0111			
	(0.035)	(0.021)			
41≤WH≤50	-0.1341***	-0.0001			
	(0.017)	(0.015)			
WH≥51	0.0694***	0.0006			
	(0.026)	(0.019)			
WH			0.0008	-0.0005	-0.0007
			(0.001)	(0.000)	(0.001)
N	4082	4082	4082	4082	2603
Adj. R^2	0.031	0.624	0.0001	0.624	0.640

Note: The dependent variable is time spent on preparing and cooking for the family; WH = weekly work hours. Specifications (1) and (2) include work hour dummies (with 31≤WH≤40 as the reference); (2) also includes individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1991 as the reference); (3)–(5) include actual weekly work hours, with (5) regressed only including employees who work 41 hours per week or more. Specifications (4) and (5) include the same controls as (2). Robust standard errors are in parentheses; *p< 0.1, **p< 0.05, ***p< 0.01.

5.4.7 WH and physical activity

As emphasized by Berniell (2012), the influence of working hours on the (im) probability of physical activity could affect health, and we do in fact observe a significant negative effect of long work hours on the likelihood of sports

[70] We also show that females spend more time on food preparation and cooking, which is the case in most Chinese families.

participation (see Table 5.12).[71] This result echoes Xu (2013) findings for the U.S.

Table 5.12 Probit estimates for long work hours on leisure time/sports: 1997–2009

Variables	(1)	(2)	(3)	(4)	(5)
$11 \leq WH \leq 30$	-0.336***	-0.081			
	(0.077)	(0.083)			
$41 \leq WH \leq 50$	-0.229***	-0.026			
	(0.047)	(0.053)			
$WH \geq 51$	-0.578***	-0.216***			
	(0.048)	(0.059)			
WH			-0.014***	-0.006***	-0.008**
			(0.002)	(0.002)	(0.003)
N	6822	6822	6822	6822	3086
Pseudo R^2	0.025	0.101	0.014	0.101	0.108

Note: The dependent variable is a dummy for sports participation; WH =weekly work hours. Specifications (1) and (2) include work hour dummies (with $31 \leq WH \leq 40$ as the reference), as well as individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1997 as the reference); (3)–(5) include actual weekly work hours, with (5) regressed only including employees who work 41 hours per week or more. Specifications (4) and (5) include the same controls as (2). Robust standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.

The results related to sedentary activities (e.g., watching TV, reading, writing, or drawing) show that working longer hours (41–50 and over 50 hours per week) significantly reduces the time spent watching TV (see Table 5.13). When regressed only on individuals working over 40 hours per week, however, this significance diminishes although it still remains negative (column 3). In contrast, we find no association between long work hours and time spent reading, writing, or drawing (columns 4–6).

Table 5.13 OLS estimates for long work hours on sedentary activities: 2004–2009

	Watching TV			Reading, writing, and drawing		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$11 \leq WH \leq 30$	0.208			0.176		
	(0.178)			(0.139)		
$41 \leq WH \leq 50$	-0.263**			0.035		

[71] Males are more likely to perform sports activities than females. In addition, a higher household income level is associated with an increased probability of physical activity.

	(0.125)			(0.106)		
WH≥51	-0.474***			-0.083		
	(0.122)			(0.109)		
WH		-0.014***	-0.007		-0.004	-0.005
		(0.004)	(0.006)		(0.003)	(0.005)
N	4055	4055	1953	2096	2096	839
Adj. R^2	0.062	0.061	0.042	0.050	0.051	0.066

Note: The dependent variable is time (hours/week) spent watching TV/reading, writing, or drawing; WH =weekly work hours. Specifications (1) and (4) include work hour dummies (with 31≤WH≤40 as the reference), as well as individual characteristics, family characteristics, provincial dummies (with Liaoning as the reference), and year dummies (with 1991 as the reference); (2), (3), (5) and (6) include weekly work hours, with (3) and (6) regressed only including employees who work 41 hours per week or more. Specifications (2), (3), (5) and (6) include the same controls as (1). Robust standard errors are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.

In sum, the results for the impact of long work hours on lifestyles suggest that a long work week negatively affects sleep time, fat intake, the probability of sports participation, and watching TV, although the magnitudes are small. We find no evidence that working hours are associated with calorie intake or with time spent preparing food, cooking, reading, writing, or drawing.[72]

5.5 Conclusions

This analysis of data from the China Health and Nutrition Survey (CHNS) assesses whether any association exists between long work hours and health among 18- to 65-year-old Chinese working more than 11 hours per week. Our study extends the existing literature by using a rich set of health measures, including objective and subjective measures of health, plus a wealth of multilevel confounding factors. We also overcome the potential biases associated with individual time-invariant unobservables by adopting both fixed-effects and fixed-

[72] We conducted a number of robustness test, including partitioning the sample into different employment sectors (state-owned, collective, and private enterprises), different firm sizes, and rural versus urban individuals. Additionally, as in Frijters et al. (2009), we looked specifically at extremely long work hours (60 hours and more per week). The results were qualitatively similar although some are worth reporting: (i) employees working longer hours in private (rather than state-owned or collective) enterprises are more likely to report ill health; (ii) long work hours also appear to have a stronger association with SRH in urban than in rural areas; and (iii) we find no significant results for extremely long work hours and health. These results are available from the author upon request.

effects ordered logit approaches. Finally, we identify certain pathways through which long work hours might affect individual lifestyles.

The study yields the following main findings. First, working more than 50 hours per week (as opposed to 31–40 hours per week) increases the probability of high blood pressure, although the effect is not very strong: systolic blood pressure about 1 mm Hg higher and diastolic blood pressure around 0.5 mm Hg higher. Second, long work hours do not seem to lead to either general or central obesity. Third, self-reported health is indeed poorer for individuals working long hours than for those working 31–40 hours per week, although here again, the effect is not strong: an approximately -0.12 effect on a 4-scale measure of self-reported health. Finally, long work hours have diverse impacts on different aspects of individual lifestyles. Specifically, they slightly decrease daily sleep time and the probability of sports participation or watching TV. Nonetheless, they do not seem to be associated with diet – not even calorie intake or time spent on food preparation and cooking–or with the sedentary activities of reading, writing, or drawing.

Our analysis is, of course, subject to certain limitations: first, we are unable to take shift work into consideration, which, as Bannai and Tamakoshi (2014) point out, may eliminate the significant negative effects of long work hours noted in other studies. Second, although we restrict our analysis to those working more than 11 hours per week, we cannot completely rule out the endogeneity of long work hours. Third, the potential impact of consistently working long hours on health is still unclear. Further studies thus are needed to clarify this aspect.

Despite these methodological shortcomings, our results do enable tentative conclusions on how long work hours might influence health by affecting individual lifestyles. For example, our findings indicate that long work weeks, especially those over 50 hours long, may shorten the time available for recovery and reduce daily sleep time, leading to insufficient rest that could increase the odds of high blood pressure (Cappuccio et al., 2007; Gangwisch et al., 2006). Likewise, irregular lifestyles associated with long work hours may reduce the probability of physical activity, which can lead to physiological changes (van der Hulst, 2003) like hypertension (high blood pressure in our analysis). Contrary to findings in other studies, however, we find no positive association between long work hours and obesity. On the one hand, there is a slight indication that long work hours could be associated with a lower fat intake and less time spent on sedentary activity like watching TV. On the other, long work hours appears to decrease the probability of sports participation. These effects could thus counterbalance each other, resulting in no pronounced association between long work hours and obesity – or perhaps even a negative impact of the former on the latter.

Overall, however, our results provide limited evidence that long work hours in China are seriously affecting health or lifestyles, at least in terms of the health measures used in this study. Three possible explanations for this observation come to mind: First, there is a deeply rooted long work hours culture in China (Sartor, 2011), thereby making Chinese workers perhaps more resilient to the adverse effects of long work hours – at least in comparison to Western workers. Second, and related to this long work hours culture, is the fact that, contrary to Western settings, a Chinese worker’s job is not the primary source of stress. As pointed out by Xie (2006), the dramatic and rapid change in the social environment has overshadowed the workplace as a major source of stress. A further source of stress in many Western countries is the difficulty to balance work and family life (Spector et al., 2004). Due to the active involvement of the extended family in caring for children, as well as the small family sizes, balancing work and family may be less of a source of stress in China than in Western countries. Third, there is growing evidence that the detrimental effects of working hours are not primarily associated with the length of the work week per se, but, instead, with the extent to which actual work hours deviate from desired work hours (Bassanini and Caroli, 2014; Bell et al., 2012). Especially in emerging countries, desired work hours may be substantially longer than in more developed countries, and there is ample empirical evidence that the extent of underemployment is more pronounced in emerging economies despite long actual work hours (e.g. Otterbach, 2010). Although we do not have the data to analyze such hours constraints, desired working time in China may be considerably longer than in other countries, which would dampen the negative effects of long work hours in China. As emphasized by Verité (2004), Chinese workers' desire for overtime is quite pronounced. Moreover, according to recent media reports, Chinese employees have been striking for longer work hours in order to increase their wage earnings (Luk and Wong, 2014; Slaten, 2014).

However, further research is needed to assess whether the long work weeks in China are influencing other health and lifestyle measures, or whether – as our study appears to indicate –the prominent media attention to "*Guolaosi*" is unfounded.

Chapter 6 Summary

Chapter 6 presents conclusions and discussions of the preceding 4 studies from Chapter 2 to Chapter 5, specifically:

6.1 Summary

In Chapter 2, we find no association of maternal employment and childhood adiposity. Moreover, maternal employment is also not associated with either diet or physical activity of children. However, our results are well consistent with some recent evidence in Europe (Greve, 2011; Gwozdz et al., 2013), supporting the evidence that maternal employment might not necessarily be detrimental to child adiposity. One tentative explanation is that, the major source of informal childcare in China is grandparents, who are prone to provide childcare with a high quality.

In Chapter 3, our findings provide strong evidence that calorie-income elasticities are small, irrespective of using parametric, nonparametric, or semiparametric techniques. Furthermore, these elasticities remain small when taking nonlinearities into consideration, and also for sub-analysis for gender, individuals with differences in calorie intake or even impoverished households. Although calorie-income are small, however, our results are well in line with some prior studies (Bishop et al., 2010; Lu and Luhrmann, 2012; Shankar, 2010; Zhong et al., 2012), suggesting that households might be quite successful in maintain calorie intake stable as income changes. Also note, despite the marked increase in income, the Chinese demand for better food quality, food diversity and also food safety has also enhanced (Gale and Huang, 2007; Liu et al., 2013b), instead of increased demand for calorie intakes.

Chapter 4 provides further evidence that peer effects exist not only among adolescents but also children, suggesting that the formation of health lifestyles associated with peers is important for young children. In addition, we find that the magnitudes of peer effects change greatly over the distribution of individual BMI and stronger effects are observable at the upper end than at the bottom or median. This finding implies that obese individuals are more vulnerable to peers. Furthermore, females are more susceptible compared with males, which mirrors some U.S studies among adolescents (see, for instance, Trogdon et al., 2008). More importantly, we find that community-level average peer BMI is associated with self-perceived bodyweight in adolescents, providing evidence that a higher average peer BMI is related to the probability of a self-assessed perception of overweigh, in particular, for adolescent girls. All in all, as have mentioned previously, our results support the existence of peer effects on childhood and adolescent obesity, but the magnitudes fall within the broader range for the U.S. adolescent studies using similar specification to ours. Therefore, it also implies that peer effects do not necessarily stronger within a collectivistic society like China in comparison to the counterparts in an individualistic society like the U.S.

In Chapter 5, we reveal that working above 50 hours per week (31-40 hours per week as the comparison), increases the probability of suffering from high blood pressure, though the effects are relatively small. Also, self-evaluated health is poorer for individuals working long hours compared with those weekly working

31-40 hours but the effect is not so strong. Eventually, long work hours have various impacts of different aspects of individual lifestyles. Specifically, we cannot find a positive correlation between long work hours and obesity. Nevertheless, long work hours seem to be related to a decreased fat intake and less time spent on sedentary activity like watching TV. But, long work hours decrease the probability of sports participation. In summary, we provide limited evidence that long work hours in China have deleterious influences on health or lifestyles. Therefore, further research needs to explore the potential impacts of long work hours on other health or lifestyle measures.

6.2 Limitations

Several limitations should be mentioned: In Chapter 2, a causal examination is impossible in our cross-sectional case. In addition, some biases from self-reported data (e.g. physical and sedentary activities) should be taken into account. More importantly, we adopt some Western growth charts for waist circumference, which may lead to some biases in assessing central obesity in children. In Chapter 3, it is important to note that, the issue of endogeneity in relation between income and calorie intake remain unresolved. In Chapter 4, despite controlling for a rich set of household and community characteristics, we still cannot rule out correlated effects, which would lead to an upward bias. One point should be highlighted that the examination of mechanism of peer effects cannot either claim to be causal. It also needs further investigations. In Chapter 5, firstly, shift work is not taken into account, which, as highlighted by Bannai and Tamakoshi (2014), might eliminate the significant negative impacts stemming from long work hours. Secondly, the issue of endogeneity of long work hours cannot be ruled out, even when restricting weekly work hours above 11. Lastly, some potential measurement errors emanated from self-reported working hours may exist in our analysis.

Contributions

For each of above-mentioned four studies in the dissertation, first author (Peng Nie) has contributed to the most, especially for data preparation, analysis and conceptual decision as well.

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Appendix

Table A2.1 Descriptive statistics

Variables	Obs	Mean	SD	Obs	Mean	SD	T-test
	Employed mothers			Non-employed mothers			MD
Obesity							
BMI *z*-score	2064	-0.119	1.172	554	-0.044	1.267	0.163***
WC *z*-score	1721	-0.312	1.779	445	-0.259	1.879	0.053
Diet							
Meals at home	1431	2.703	0.588	341	2.664	0.644	-0.039
Caloric intake	2064	1526.859	622.06	554	1570.597	622.21	43.738
Physical activity							
Physical exercise	443	57.038	46.034	132	59.371	61.553	2.333
Sedentary activity	724	489.365	215.708	229	501.41	181.722	12.046
Child characteristics							
Age: child	2064	8.621	3.44	554	9	3.582	0.379**
Gender: child	2064	0.56	0.496	554	0.536	0.499	-0.024
Birth order	2064	0.853	0.354	554	0.892	0.311	0.039**
Number of siblings	2064	0.328	0.581	554	0.224	0.442	-0.104***
Family characteristics							
Age: mother	2064	34.982	5.225	554	35.891	6.585	0.909***
Age: father	2060	36.312	5.535	554	37.935	7.195	1.622***
Job status: father	2064	0.959	0.199	554	0.699	0.459	-0.260***
BMI: mother	2064	22.538	3.098	554	22.787	3.219	0.248*
BMI: father	2064	22.931	3.11	554	23.387	3.1	0.456***
Household size	2064	4.391	1.348	554	4.363	1.277	-0.028
Socioeconomic characteristics							
Household income	2064	9.672	1.016	554	9.505	1.162	-0.168***
Education: mother	2064	8.439	4.04	554	8.347	3.012	-0.092
Education: father	2064	9.318	3.669	554	9.323	3.330	0.005

Source: China Health and Nutrition Survey, authors' calculations.

Notes: The age group for BMI and waist circumference (WC) is 3 to 17 year-old Chinese children. The BMI *z*-score designates the *z*-score of body mass index (BMI) based on the IOTF growth references. The WC *z*-score designates the *z*-score of waist circumference based on the British 1990 growth reference. "Meals at home" refers to the ratio of meals taken at home (over 3 days) to total meal times. "caloric intake" means the 3-day average calorie intake, "physical exercise" means time spent on physical exercises per week before/after school, and "sedentary activity" means the total time spent watching TV, doing homework, and reading and writing (measured in minutes per week). Household income means translog household net income. Asterisks denote statistically significant difference between employed and non-employed. Obs means observations. SD means standard deviation. MD means mean difference; $^{*}p<0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table A2.2 OLS estimates of maternal working hours on obesity measures

Variables	BMI z-score		
	3-17	6-17	3-5
DWH=1 (0<MWH<20)	0.031	0.031	-0.284
	(0.170)	(0.177)	(0.535)
DWH=2 (20≤MWH<30)	0.177	0.077	0.878
	(0.170)	(0.178)	(0.544)
DWH=3 (30≤MWH<40)	0.160	0.103	0.515
	(0.172)	(0.181)	(0.604)
DWH=4 (40≤MWH<50)	0.081	0.020	0.618
	(0.156)	(0.165)	(0.479)
DWH=5 (50≤MWH<60)	0.115	0.012	0.801
	(0.171)	(0.178)	(0.596)
DWH=6 (MWH≥60)	0.185	0.135	0.426
	(0.179)	(0.184)	(0.659)
Observations	1211	1062	149
Adj. R^2	0.129	0.152	0.141

Source: China Health and Nutrition Survey, authors' calculations.
Notes: The dependent variable is BMI z-score. DWH indicates dummies of maternal working hours (non-working mothers as the reference group). MWH indicates maternal working hours. Controls include child, family and socioeconomic characteristics, dummies of year (1997 as the reference year), province (Liaoning as the reference) and urban (rural as the reference). 3-17 means 3≤child age≤17, 6-17 means 6≤child age≤17, and 3-5 means 3≤child age<6. Robust standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Tables A2.3 OLS estimate of grandmother childcare hours on obesity measure

Variables	BMI z-score (3-6 year olds)
Dummy of grandmother childcare hours (0<GCH<6)	-0.242
	(0.314)
Dummy of grandmother childcare hours (6≤GCH<20)	-0.248
	(0.312)
Dummy of grandmother childcare hours (GCH≥20)	-0.331
	(0.324)
N	169
R^2	0.079

Source: China Health and Nutrition Survey, authors' calculations.
Notes: The dependent variable is BMI z-score. GCH indicates grandmother childcare hours (no grandmother childcare as the reference group). Controls include child, family and socioeconomic characteristics, dummies of year (1997 as the reference year), province (Liaoning as the reference) and urban (rural as the reference). Standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Table A3.1 Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
		Dependent variable			
Calorie intake	45398	2452.056	879.572	205.824	54230.390
		Independent variables			
Individual variables					
Hhinc11	45398	6118.445	5928.921	218.307	39079.280
Age	45398	40.175	11.245	18	59.99
Education	45398	7.831	4.390	0	21
Gender	45398	0.486	0.500	0	1
Urban	45398	0.317	0.465	0	1
Medical insurance	45398	0.388	0.487	0	1
Activity level	45398	2.144	0.894	1	3
Household variables					
Household size	45398	4.124	1.447	1	13
Water	45398	0.861	0.346	0	1
Sanitation	45398	0.354	0.478	0	1
Electricity	45398	0.990	0.101	0	1
Community variables (20 food prices)					
Rice	45398	3.228	0.880	1.370	7.130
Bleached flour	45398	3.796	1.027	1.380	8.250
Unbleached flour	45398	3.228	0.834	1.190	7.730
Corn flour	45398	3.307	1.435	0.800	10.310
Millet	45398	5.069	1.994	0.250	12.880
Sorghum	45398	4.213	2.185	0.550	12.930
Rapeseed oil	45398	12.091	3.718	1.070	30.920
Soybean oil	45398	11.497	3.123	4.680	21.480
Peanuts oil	45398	14.880	4.693	6.130	50.210
Sugar	45398	6.929	1.645	2.610	13.140
Eggs	45398	11.231	4.525	3.600	26.160
Vegetable	45398	1.732	1.005	0.130	7.280
Pork	45398	17.692	3.890	6.220	29.620
Chicken	45398	18.708	7.449	5.130	64.170
Beef	45398	24.634	9.463	5.770	68.230
Mutton	45398	26.966	10.220	8.420	66.990
Fresh milk	45398	4.200	3.430	0.510	20.250
Milk powder	45398	35.990	15.322	10.440	134.480
Fish	45398	12.341	4.884	1.640	41.930
Beancurd	45398	2.890	1.027	0.770	9.280

Source: China Health and Nutrition Survey 1991, 1993, 1997, 2000, 2004, 2006, and 2009.

Note: The sample is restricted to individuals aged ≥18 to<60. Calorie intake (kcal) means 3-day average calorie intake per capita. Hhinc11 designates annual household per capita income level (inflated to 2011). The model includes dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2= moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market: rice, bleached flour, unbleached flour, corn flour, millet, sorghum, rapeseed oil, soybean oil, peanut oil, sugar, eggs, commonly eaten vegetables, pork, chicken, beef, mutton, fresh milk, milk powder, fish, and beancurd.

Table A3.2 Summary of annual per capita income (in yuan, adjusted to 2011) by residence (urban versus rural)

Year	1991	1993	1997	2000	2004	2006	2009
All	3116.889	3443.302	4354.863	5493.495	7285.508	8075.195	10898.32
	(7117)	(6291)	(5906)	(6128)	(6806)	(6504)	(66460
Urban	4111.125	4844.714	5434.832	7061.786	9832.865	10433.440	13128.890
	(2250)	(1885)	(1839)	(1885)	(2214)	(2144)	(2175)
Rural	2657.257	2843.741	3866.527	4796.765	6057.318	6915.545	9813.224
	(4867)	(4406)	(4067)	(4243)	(4592)	(4360)	(4471)

Source: China Health and Nutrition Survey 1991, 1993, 1997, 2000, 2004, 2006, and 2009.
Note: Sample is restricted to individuals aged ≥18 to <60. Annual per capita income is adjusted to 2011. Observations are in parentheses.

Table A3.3 Summary of individual calorie intake (kcal/person/day) by residence and gender

Year	1991	1993	1997	2000	2004	2006	2009
All	2741.816	2677.233	2450.292	2420.693	2347.333	2262.992	2251.363
	(7117)	(6291)	(5906)	(6128)	(6806)	(6504)	(6646)
Urban	2547.673	2496.702	2403.634	2337.594	2316.14	2198.955	2130.553
	(2250)	(1885)	(1839)	(1885)	(2214)	(2144)	(2175)
Rural	2831.568	2754.469	2471.390	2457.611	2362.373	2294.482	2310.133
	(4867)	(4406)	(4067)	(4243)	(4592)	(4360)	(4471)
Male	2949.650	2868.994	2639.843	2607.503	2530.989	2462.392	2454.695
	(3429)	(3052)	(2938)	(3103)	(3262)	(3108)	(3194)
Female	2548.577	2496.544	2262.657	2229.067	2178.292	2080.502	2063.228
	(3688)	(3239)	(2968)	(3025)	(3544)	(3396)	(3452)

Source: China Health and Nutrition Survey 1991, 1993, 1997, 2000, 2004, 2006, and 2009.
Note: Sample is restricted to individuals aged ≥18 to<60. Observations are in parentheses.

Table A3.4 Summary of individual calorie intake (kcal/person/day) by activity level

Activity level	1991	1993	1997	2000	2004	2006	2009
1 (light)	2430.789	2364.035	2273.312	2292.735	2245.465	2110.375	2155.429
	(1929)	(1497)	(1759)	(1906)	(2663)	(2555)	(3045)
2 (moderate)	2601.137	2545.112	2340.223	2405.899	2298.729	2206.986	2283.813
	(1302)	(1164)	(1037)	(996)	(1287)	(1193)	(1161)
3 (heavy)	2943.343	2848.761	2587.093	2500.862	2464.220	2428.722	2355.643
	(3886)	(3630)	(3110)	(3226)	(2856)	(2756)	(2440)

Source: China Health and Nutrition Survey 1991, 1993, 1997, 2000, 2004, 2006, and 2009.
Note: Sample is restricted to individuals aged ≥18 to<60. Activity intensity is recoded into the three levels (1=light, 2=moderate, and 3=heavy) based on age and gender-specific recommended daily allowances (RDAs) by the Chinese Nutrition Society (2011). Observations are in parentheses.

Table A3.5 Means and RDIs of individual calorie intake (kcal/person/day) by activity level

Activity level	Male	RDIs	Female	RDIs	Male	RDIs	Female	RDIs
Age group	≥18 to <50				≥50 to <60			
Light	2487.65	2400	2104.89	2100	2397.04	2300	2076.83	1900
Moderate	2566.93	2700	2158.796	2300	2483.58	2600	2118.69	2000
Heavy	2828.55	3200	2473.44	2700	2692.83	3100	2330.92	2200

Source: China Health and Nutrition Survey 1991, 1993, 1997, 2000, 2004, 2006, and 2009.
Note: RDIs is based on the *2011 Chinese Dietary Guideline.*

Tables A3.6 OLS estimates of calorie-income elasticity (LLS and LLI models)

Variables	(1) LLS	(2) LLI
LogINC	-0.0496**	0.0173***
	(0.021)	(0.003)
Squared term of LogINC	0.0038***	-
	(0.001)	
Inverse term of household per capita	-	11.2269**
		(5.548)
Constant	7.8923***	7.5990***
	(0.093)	(0.050)
N	45398	45398
Adj. R^2	0.167	0.167

Note: LLS=regression model logci-loghhinc11+squared loghhinc11; LLI=regression model logciloghhinc11+inverse hhinc11. The OLS estimates include age, education level, and dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2= moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity, as well as the prices (in yuan per kilogram, inflated to 2011) of 20 different foods on the free market. Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Tables A3.7 OLS estimates of calorie-income elasticity (a control for BMI)

Variables	(1)	(2)	(3)
logINC	-0.012***	0.007***	0.012***
	(0.002)	(0.002)	(0.002)
BMI	0.002***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)
Constant	8.036***	7.381***	7.549***
	(0.025)	(0.041)	(0.056)
N	41544	41544	41544
Adj. R^2	0.118	0.158	0.180

Note: (1) contains household per capita income (inflated to 2011), age, education level, BMI, and dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2= moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity. (2) contains the same regressors as (1) but introduces the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. (3) contains the same regressors as (2) but introduces a year dummy (with 1991 as the base year) and a province dummy(with Liaoning as the base province).Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Tables A3.8 OLS estimates of calorie-income elasticity (a control for household assets)

Variables	(1)	(2)	(3)
logINC	-0.001	0.009***	0.013***
	(0.002)	(0.002)	(0.002)
VCR	0.007	-0.008	-0.015**
	(0.006)	(0.006)	(0.006)
TV	-0.101***	-0.049***	-0.014***
	(0.004)	(0.004)	(0.004)
Washing machine	-0.020***	-0.025***	-0.026***
	(0.004)	(0.004)	(0.004)
Refrigerator	-0.000	0.003	0.001
	(0.004)	(0.004)	(0.004)
Air-conditioner	-0.009*	0.017***	-0.002
	(0.005)	(0.005)	(0.005)
Sewing machine	0.009***	0.003	-0.002
	(0.003)	(0.003)	(0.003)
Fan	0.028***	0.034***	0.005
	(0.004)	(0.004)	(0.004)
Camera	0.017***	0.008*	0.006
	(0.005)	(0.005)	(0.005)
Constant	7.975***	7.633***	7.683***
	(0.023)	(0.039)	(0.054)
N	45114	45114	45114
Adj. R^2	0.138	0.162	0.179

Note: (1) contains household per capita income (inflated to 2011), age, education level, availability of VCR, TV, washing machine, refrigerator, air-conditioner, sewing machine, fan, and camera, as well as dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2= moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity.(2) contains the same regressors as (1) but introduces the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. (3) contains the same regressors as (2) but introduces a year dummy (with 1991 as the base year) and a province dummy(with Liaoning as the base province).Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Tables A3.9 OLS estimates of calorie-income elasticity (a control for poverty)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Poor	Nonpoor	Poor	Nonpoor	Poor	Nonpoor
logINC	0.002	-0.013**	0.011***	0.007	0.013***	0.010*
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)
Constant	8.024***	7.893***	7.418***	7.613***	7.650***	7.663***
	(0.028)	(0.079)	(0.048)	(0.093)	(0.067)	(0.121)
N	29946	15452	29946	15452	29946	15452
Adj. R^2	0.117	0.094	0.169	0.115	0.192	0.130

Note: (1) and (2) contain household per capita income (inflated to 2011), age, education level, and dummies for gender (1=male, 0=female), urban residence (1=urban, 0=rural), activity level (1=light, 2= moderate, and 3=heavy), availability of medical care, water, sanitation, and electricity.(3) and (4) contain the same regressors as (1) but introduce the prices (in yuan per kilogram, inflated to 2011) of 20 different foods in the free market. (5) and (6) contain the same regressors as (3) but introduce a year dummy (with 1991 as the base year) and a province dummy (with Liaoning as the base province).Robust standard errors are in parentheses; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table A4.1 Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variable					
BMI	2186	16.61	2.77	10.79	30.48
Self-reported perception of weight	776	0.93	0.54	0	2
BMI *z*-score (based on IOTF)	2186	-0.15	1.20	-4.49	4.82
Independent variables					
Average peer BMI	2186	16.61	1.91	12.14	24.05
Age	2186	9.13	3.28	3	17.77
Gender dummy	2186	0.54	0.50	0	1
Family and mother variables					
Mother’s BMI	2186	22.61	3.09	15.57	36.53
Mother’s education	2186	8.26	3.81	0	21
Mother’s employment status	2186	0.76	0.43	0	1
Log(household income, in yuan)	2186	8.44	1.08	0.76	11.59
Household size	2186	4.54	1.42	2	13
Urban dummy	2186	0.24	0.43	0	1
Community variables					
Public school dummies					
Primary school	2186	0.73	0.44	0	1
Low middle school	2186	0.34	0.48	0	1
Upper middle school	2186	0.15	0.36	0	1
Fast food restaurant dummy					
Fast food restaurants	2186	0.15	0.35	0	1
Recreation facilities dummies					
Gym/exercise centers	2186	0.12	0.33	0	1
Park/public recreation places	2186	0.17	0.38	0	1
Playgrounds	2186	0.32	0.47	0	1
Free market food price dummies (yuan/kilograms, inflated to 2011)					
Rice	2186	3.72	0.69	1.85	5.67
Bleached flour	2186	4.03	1.15	1.43	7.78
Unbleached flour	2186	3.50	0.90	1.19	7.73
Corn flour	2186	3.80	1.59	1.41	10.31
Millet	2186	5.99	2.14	2.24	12.88
Sorghum	2186	4.55	2.31	0.55	12.93
Rapeseed oil	2186	12.36	4.63	1.07	30.92
Soybean oil	2186	11.22	3.01	4.68	21.29
Peanut oil	2186	16.07	5.65	6.57	50.2
Sugar	2186	6.11	1.32	3.09	11.39
Eggs	2186	9.70	2.64	4.39	19.39
Vegetables	2186	2.23	1.09	0.32	7.28
Pork	2186	19.66	4.03	9.36	28.38
Chicken	2186	19.81	8.28	6.67	49.53
Beef	2186	31.05	10.38	9.37	68.23
Mutton	2186	31.51	11.36	11.45	66.99
Fresh milk	2186	2.44	1.28	0.51	12.82
Milk powder	2186	45.27	19.98	10.44	134.48
Fish	2186	12.10	3.92	1.64	27.64
Beancurd	2186	3.35	1.13	1.07	9.28

Source: China Health and Nutrition Survey 2004, 2006, and 2009.

Note: The age group is restricted to 3- to 18-year-olds. The BMI *z*-score is calculated based on IOTF criteria. Self-reported perception of weight is restricted to adolescents aged 10–17.99.

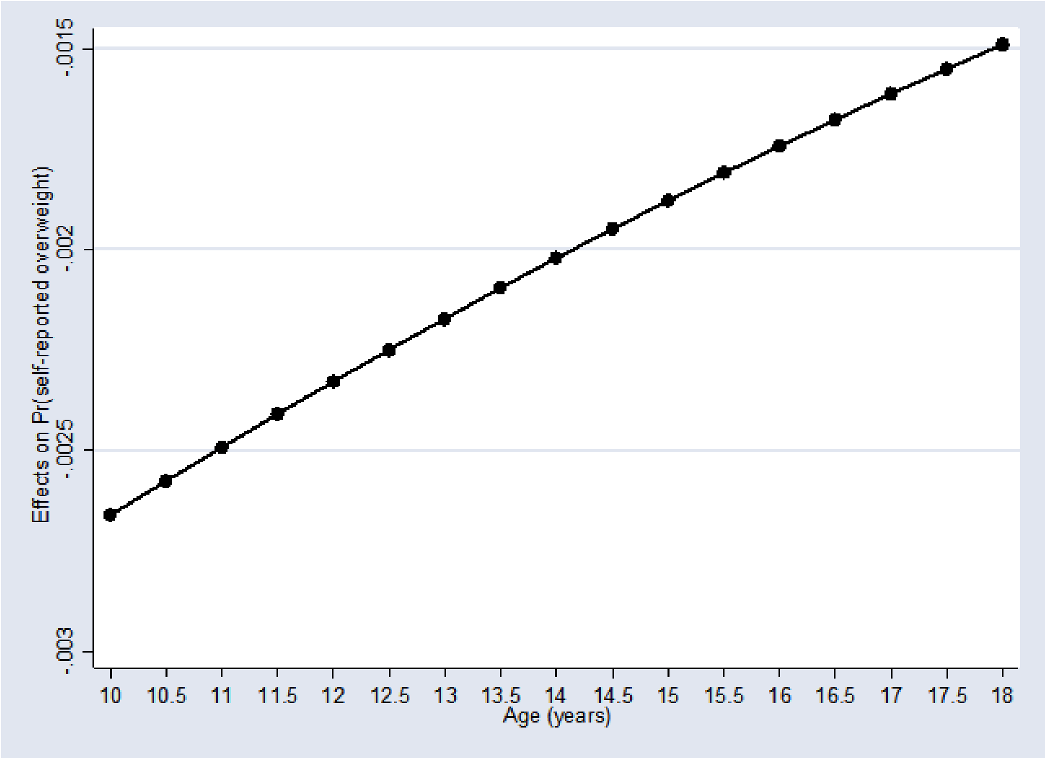

Figure A4.1 Marginal effects of peers on probability of self-reported overweight for different adolescent ages

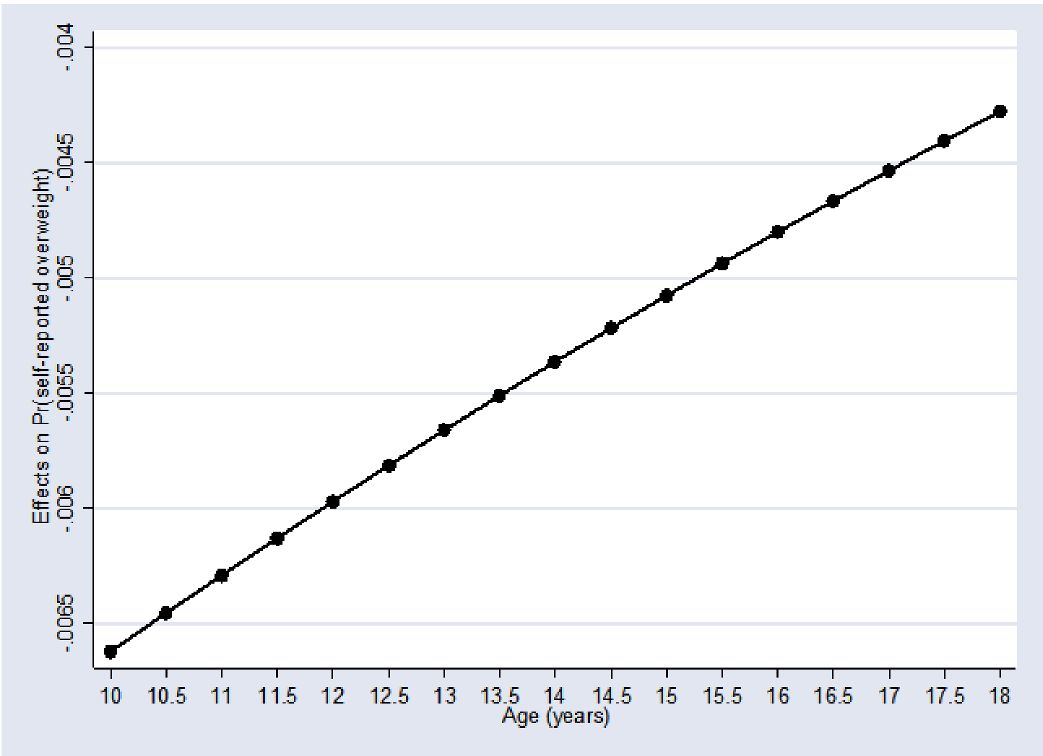

Figure A4.2 Marginal effects of peers on probability of self-reported overweight for different female adolescent ages

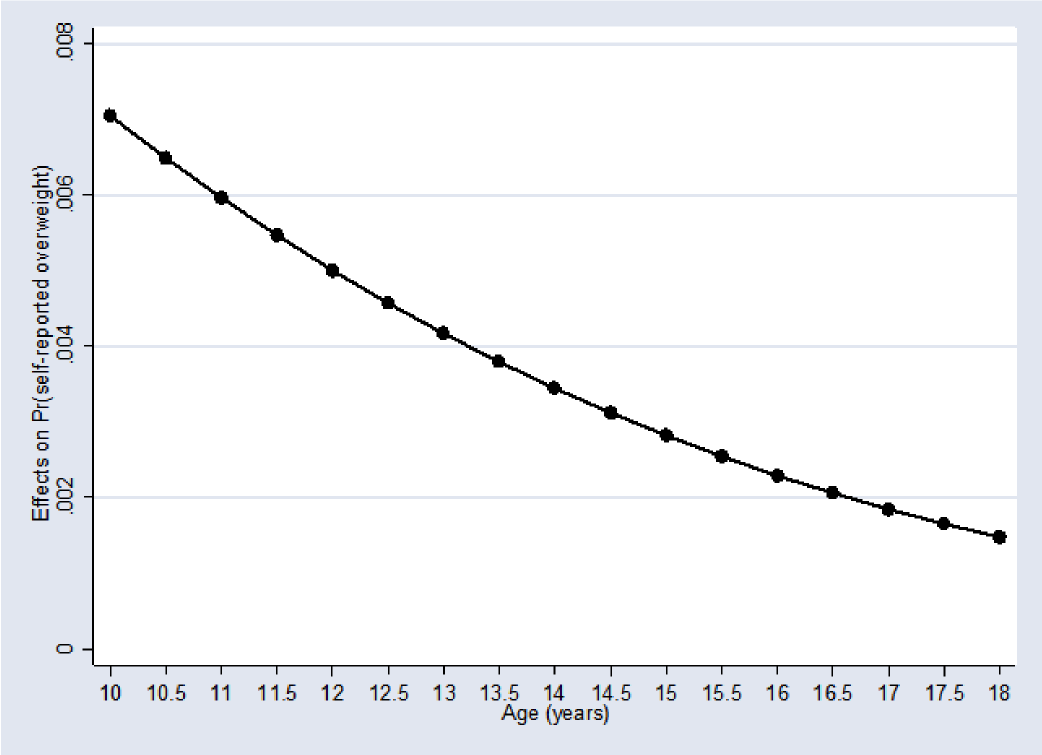

Figure A4.3 Marginal effects of peers on probability of self-reported overweight for different male adolescent ages

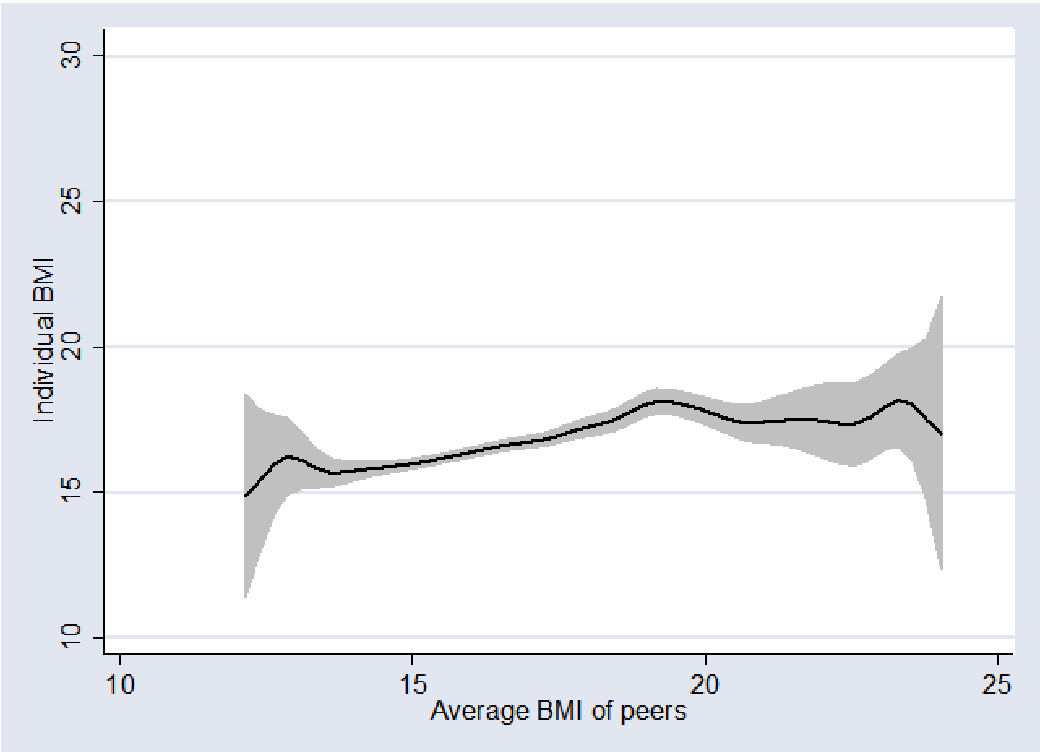

Figure A4.4 Semiparametric estimate of average peer effects (nonparametric part)

Table A4.2 OLS estimates of peer effects on individual bodyweight (double log model, 3- to 18-year-olds)

	(1) All	(2) All	(3) All	(4) Urban	(5) Rural	(6) Male	(7) Female
APB	0.596***	0.369***	0.281***	0.153*	0.281***	0.186***	0.367***
(log)	(0.030)	(0.036)	(0.039)	(0.080)	(0.047)	(0.050)	(0.060)
CI	[0.537,0.655]	[0.299,0.440]	[0.204,0.359]	[-0.004,0.309]	[0.189,0.373]	[0.088,0.285]	[0.249,0.486]
N	2186	2186	2186	528	1658	1191	995
Adj. R^2	0.179	0.255	0.261	0.258	0.253	0.280	0.252
Children: 3–9 years							
APB	0.434***	0.360***	0.253***	0.119	0.241***	0.171**	0.342***
(log)	(0.049)	(0.050)	(0.057)	(0.141)	(0.065)	(0.072)	(0.088)
CI	[0.338,0.530]	[0.262,0.459]	[0.142,0.364]	[-0.158,0.396]	[0.112,0.369]	[0.030,0.312]	[0.170,0.514]
N	1237	1237	1237	303	934	685	552
Adj. R^2	0.084	0.137	0.149	0.170	0.138	0.141	0.159
Adolescents: 10–18 years							
APB	0.529***	0.278***	0.140**	-0.186	0.145**	0.062	0.201**
(log)	(0.045)	(0.053)	(0.058)	(0.133)	(0.069)	(0.084)	(0.084)
CI	[0.441,0.617]	[0.173,0.382]	[0.026,0.254]	[-0.448,0.076]	[0.009,0.280]	[-0.103,0.227]	[0.037,0.366]
N	949	949	949	225	724	506	443
Adj. R^2	0.135	0.226	0.237	0.145	0.250	0.249	0.251

Note: The dependent variable is the translog BMI of children aged 3 to 18 years. All models are in log-log forms. APB=average peer BMI. (1) includes average peer BMI without control, (2) includes individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size) as well as an urban dummy. (3) includes the same controls as (2) plus year dummies(with 2004 as the base year) and province dummies(with Liaoning as the base province), as well as dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). (4) and (5) include the same controls as (3) but for urban and rural areas, respectively. (6) and (7) include the same controls as (3). CI =95% confidence intervals; robust standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table A4.3 Quantile regressions of peer effects on individual bodyweight (double log model, 3- to 18-year-olds)

	25%	50%	75%
Average peer BMI(log)	0.233***	0.310***	0.359***
	(0.042)	(0.045)	(0.061)
CI	[0.151,0.315]	[0.221,0.399]	[0.239,0.479]
N	2186	2186	2186
Pseudo R^2	0.150	0.186	0.206
Males	25%	50%	75%
Average peer BMI (log)	0.278***	0.303***	0.267***
	(0.055)	(0.059)	(0.086)
CI	[0.171,0.386]	[0.187,0.419]	[0.097,0.436]
N	1191	1191	1191
Pseudo R^2	0.169	0.198	0.223
Females	25%	50%	75%
Average peer BMI (log)	0.274***	0.283***	0.428***
	(0.067)	(0.077)	(0.091)
CI	[0.143,0.405]	[0.133,0.433]	[0.249,0.607]
N	995	995	995
Pseudo R^2	0.159	0.203	0.212

Note: The dependent variable is the translog BMI of children aged 3 to 18 years. All models are in log-log forms. Controls include individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy, year dummies (with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). CI =95% confidence intervals; bootstrapped standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table A4.4 OLS estimates of peer effects on individual BMI (6- to 18-year-olds)

	(1) All	(2) All	(3) All	(4) Male	(5) Female
Average peer BMI	0.584***	0.406***	0.325***	0.082	0.484***
	(0.046)	(0.060)	(0.065)	(0.076)	(0.091)
CI	[0.494,0.674]	[0.288,0.525]	[0.197,0.452]	[-0.068,0.231]	[0.305,0.663]
N	1031	1031	1031	561	470
Adj.R^2	0.182	0.248	0.258	0.258	0.302
Children: 6–9 years					
Average peer BMI	0.569***	0.448***	0.390***	-0.012	0.631***
	(0.083)	(0.098)	(0.105)	(0.129)	(0.127)
CI	[0.405,0.732]	[0.255,0.642]	[0.183,0.597]	[-0.266,0.241]	[0.380,0.881]
N	459	459	459	257	202
Adj.R^2	0.163	0.232	0.225	0.203	0.386
Adolescents: 10–18 years					
Average peer BMI	0.517***	0.362***	0.227***	0.124	0.286***
	(0.056)	(0.068)	(0.070)	(0.101)	(0.102)
CI	[0.406,0.627]	[0.229,0.495]	[0.089,0.365]	[-0.074,0.322]	[0.086,0.487]
N	572	572	572	304	268
Adj.R^2	0.144	0.207	0.226	0.222	0.221

Note: Sample size is restricted to respondents aged 6 to 18. Peers are defined in the same age band and at the same school and community level. (1) includes average peer BMI, (2) includes individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy. (3) includes the same controls as (2) plus year dummies(with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). (4) and (5)include the same controls as (3). CI =95% confidence intervals; robust standard errors are in parentheses;$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table A4.5 Quantile regressions of peer effects on individual BMI (6- to 18-year-olds)

	25%	50%	75%
Average peer BMI	0.121**	0.257***	0.330***
	(0.049)	(0.082)	(0.086)
CI	[0.024,0.217]	[0.097,0.418]	[0.161,0.500]
N	1031	1031	1031
Pseudo R^2	0.182	0.207	0.219
Males	25%	50%	75%
Average peer BMI	0.062	0.121	0.166
	(0.072)	(0.098)	(0.121)
CI	[-0.080,0.204]	[-0.072,0.313]	[-0.072,0.405]
N	561	561	561
Pseudo R^2	0.207	0.221	0.238
Females	25%	50%	75%
Average peer BMI	0.217**	0.359***	0.510***
	(0.088)	(0.121)	(0.124)
CI	[0.045,0.390]	[0.122,0.596]	[0.266,0.754]
N	470	470	470
Pseudo R^2	0.225	0.244	0.279

Note: Peers are defined as those in the same age band and at the same school and community level. Controls include individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy, year dummies (with 2004 as the base year) and province dummies (with Liaoning as the base province), and dummies for public schools (primary school, lower middle school and upper middle school), fast food restaurants and recreational facilities (gym/exercise centers, park/public recreation places, playgrounds) in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). CI =95% confidence intervals; bootstrapped standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table A4.6 OLS estimates of same-gender peer effects on individual BMI (3- to 18-year-olds)

	(1) All	(2) All	(3) All	(4) Male	(5) Female
Average peer BMI	0.544***	0.358***	0.283***	0.156**	0.335***
	(0.042)	(0.048)	(0.051)	(0.063)	(0.080)
CI	[0.462,0.626]	[0.265,0.452]	[0.183,0.384]	[0.032,0.280]	[0.178,0.493]
N	1566	1566	1566	905	661
Adj. R^2	0.162	0.240	0.249	0.256	0.242
Children: 3–9 years					
Average peer BMI	0.461***	0.381***	0.312***	0.149*	0.375***
	(0.071)	(0.070)	(0.076)	(0.087)	(0.119)
CI	[0.322,0.599]	[0.244,0.519]	[0.163,0.461]	[-0.023,0.320]	[0.141,0.609]
N	895	895	895	531	364
Adj. R^2	0.105	0.160	0.162	0.154	0.199
Adolescents: 10–18 years					
Average peer BMI	0.450***	0.265***	0.109	-0.009	-0.024
	(0.059)	(0.065)	(0.067)	(0.103)	(0.092)
CI	[0.334,0.565]	[0.137,0.394]	[-0.024,0.241]	[-0.213,0.194]	[-0.205,0.158]
N	671	671	671	374	297
Adj. R^2	0.110	0.198	0.221	0.224	0.244

Note: The dependent variable is the BMI of children aged 3 to 18. Peers are defined as those in the same age group and community and of the same gender. (1) includes average peer BMI, (2) includes individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy. (3) includes the same controls as (2) plus year dummies (with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). (4) and (5) include the same controls as (3). CI =95% confidence intervals; robust standard errors are in parentheses; $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

Table A4.7 Quantile regressions of same-gender peer effects on individual BMI (3- to 18-year-olds)

	25%	50%	75%
Average peer BMI	0.198***	0.334***	0.317***
	(0.050)	(0.047)	(0.068)
CI	[0.099,0.297]	[0.242,0.427]	[0.183,0.451]
N	1566	1566	1566
Pseudo R^2	0.130	0.174	0.215
Males	25%	50%	75%
Average peer BMI	0.188***	0.287***	0.226**
	(0.069)	(0.068)	(0.090)
CI	[0.053,0.324]	[0.154,0.421]	[0.050,0.402]
N	905	905	905
Pseudo R^2	0.150	0.188	0.233
Females	25%	50%	75%
Average peer BMI	0.211***	0.263***	0.344***
	(0.075)	(0.086)	(0.126)
CI	[0.063,0.359]	[0.094,0.431]	[0.096,0.592]
N	661	661	661
Pseudo R^2	0.152	0.186	0.239

Note: The dependent variable is the BMI of children aged 3 to 18. Peers are defined as those in the same age group and community and of the same gender. Controls include individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy, year dummies(with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities, and 20 different free market food prices (yuan/kilograms, inflated to 2011). CI =95%confidence intervals; bootstrapped standard errors are in parentheses;*p<0.1, **p<0.05, ***p<0.01.

Table A4.8 OLS estimates of peer effects on individual bodyweight (using *z*-score; 3- to 18-year-olds)

	(1) All	(2) All	(3) All	(4) Urban	(5) Rural	(6) Male	(7) Female
APB	0.128***	0.143***	0.097***	0.052	0.092***	0.061**	0.125***
	(0.013)	(0.017)	(0.018)	(0.037)	(0.022)	(0.024)	(0.027)
CI	[0.102,0.155]	[0.111,0.176]	[0.061,0.132]	[-0.020,0.124]	[0.049,0.134]	[0.014,0.107]	[0.073,0.178]
N	2186	2186	2186	528	1658	1191	995
Adj. R^2	0.041	0.135	0.149	0.133	0.148	0.147	0.167
Children: 3–9 years							
APB	0.209***	0.177***	0.111***	0.061	0.098***	0.087**	0.132***
	(0.025)	(0.026)	(0.028)	(0.067)	(0.033)	(0.036)	(0.043)
CI	[0.160,0.258]	[0.127,0.227]	[0.056,0.165]	[-0.072,0.193]	[0.034,0.162]	[0.016,0.158]	[0.048,0.217]
N	1237	1237	1237	303	934	685	552
Adj. R^2	0.066	0.132	0.155	0.179	0.151	0.141	0.173
Adolescents: 10–18 years							
APB	0.135***	0.107***	0.049**	-0.056	0.049	0.013	0.077**
	(0.018)	(0.022)	(0.025)	(0.050)	(0.030)	(0.037)	(0.033)
CI	[0.100,0.171]	[0.064,0.151]	[0.001,0.098]	[-0.155,0.044]	[-0.010,0.109]	[-0.060,0.086]	[0.012,0.141]
N	949	949	949	225	724	506	443
Adj. R^2	0.057	0.151	0.166	0.101	0.171	0.178	0.162

Note: The dependent variable is the (IOTF) *z*-score of BMI for children aged 3-18 years. APB= average peer BMI.(1) includes average peer BMI without controls, (2) includes individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy. (3) includes the same controls as (2) plus year dummies (with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). (4) - (7) include the same controls as (3). CI =95% confidence intervals; robust standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Table A4.9 Quantile regressions of peer effects on individual bodyweight (using *z*-score, 3- to 18-year-olds)

	25%	50%	75%
Average peer BMI	0.076***	0.100***	0.112***
	(0.021)	(0.023)	(0.026)
CI	[0.035,0.116]	[0.054,0.146]	[0.061,0.164]
N	2186	2186	2186
Pseudo R^2	0.092	0.109	0.129
Males	25%	50%	75%
Average peer BMI	0.064**	0.095***	0.066*
	(0.029)	(0.032)	(0.034)
CI	[0.007,0.121]	[0.033,0.157]	[-0.002,0.133]
N	1191	1191	1191
Pseudo R^2	0.115	0.124	0.134
Females	25%	50%	75%
Average peer BMI	0.101***	0.104***	0.141***
	(0.031)	(0.028)	(0.034)
CI	[0.040,0.162]	[0.049,0.160]	[0.075,0.207]
N	995	995	995
Pseudo R^2	0.103	0.127	0.158

Note: The dependent variable is (IOTF) *z*-scores of BMI for children aged 3-18 years. Controls include individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy, year dummies (with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). CI =95% confidence intervals; bootstrapped standard errors are in parentheses; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table A4.10 OLS estimates of peer effects on individual bodyweight (using waist circumference, 3- to 18-year-olds)

	(1) All	(2) All	(3) All	(4) Male	(5) Female
Average peer WC	0.674***	0.217***	0.103**	0.030	0.188***
	(0.030)	(0.039)	(0.046)	(0.062)	(0.068)
CI	[0.615,0.734]	[0.140,0.294]	[0.013,0.193]	[-0.093,0.152]	[0.055,0.322]
N	1608	1608	1608	874	734
Adj. R^2	0.236	0.372	0.387	0.368	0.393
Children: 3–9 years					
Average peer WC	0.294***	0.125*	0.017	-0.058	0.108
	(0.056)	(0.064)	(0.078)	(0.104)	(0.116)
CI	[0.184,0.403]	[-0.001,0.252]	[-0.137,0.171]	[-0.263,0.146]	[-0.120,0.336]
N	678	678	678	379	299
Adj. R^2	0.041	0.112	0.125	0.122	0.095
Adolescents: 10–18 years					
Average peer WC	0.572***	0.264***	0.120**	0.037	0.200**
	(0.043)	(0.049)	(0.058)	(0.082)	(0.089)
CI	[0.488,0.656]	[0.169,0.359]	[0.006,0.235]	[-0.125,0.198]	[0.026,0.375]
N	930	930	930	495	435
Adj. R^2	0.157	0.272	0.293	0.268	0.316

Note: The dependent variable is waist circumference (WC) in cm. (1)includes average peer waist circumference, (2) includes individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy. (3) includes the same controls as (2)plus year dummies(with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). (4) and (5) include the same controls as (3). CI =95% confidence intervals; robust standard errors are in parentheses; $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

Table A4.11 Quantile regressions of peer effects on individual bodyweight (using waist circumference, 3-to 18-year-olds)

	25%	50%	75%
Average peer WC	0.073	0.103**	0.110**
	(0.069)	(0.044)	(0.052)
CI	[-0.063,0.209]	[0.017,0.189]	[0.009,0.212]
N	1608	1608	1608
Pseudo R^2	0.237	0.268	0.272
Males	25%	50%	75%
Average peer WC	0.074	0.053	0.008
	(0.077)	(0.062)	(0.096)
CI	[-0.077,0.225]	[-0.069,0.175]	[-0.179,0.196]
N	874	874	874
Pseudo R^2	0.238	0.271	0.282
Females	25%	50%	75%
Average peer WC	0.048	0.195**	0.176*
	(0.099)	(0.090)	(0.091)
CI	[-0.146,0.242]	[0.018,0.372]	[-0.003,0.355]
N	734	734	734
Pseudo R^2	0.261	0.283	0.297

Note: The dependent variable is waist circumference (WC).Controls include individual characteristics (age and gender), mother characteristics (mother's BMI, education, and employment status), and household characteristics (translog household income measured in yuan, household size), as well as an urban dummy, year dummies(with 2004 as the base year) and province dummies(with Liaoning as the base province), and dummies for public schools, fast food restaurants and recreational facilities in the community, and 20 different free market food prices (yuan/kilograms, inflated to 2011). CI=95% confidence intervals; bootstrapped standard errors are in parentheses; $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

Table A5.1 Descriptive statistics

Variable	Observatio	Mean	Std.
Dependent variables			
High blood pressure [a]	11034	0.15	0.36
Self-reported health status	5300	2.92	0.70
Daily sleep time (hours/day)	4215	7.89	1.06
Caloric intake (kcal)	10933	2393.05	883.19
Fat intake (g)	10933	81.45	70.75
Time spent on food preparation and cooking	4082	0.22	0.46
Physical activity [a]	6822	0.18	0.38
Watching TV (hours/week)	4055	4.36	2.75
Reading, writing and drawing (hours/week)	2096	1.95	1.84
Individual controls			
Weekly work hours (hours/week)	11034	46.79	11.74
Age	11034	38.71	10.43
Gender [a]	11034	0.59	0.49
Marital status [a]	11034	0.84	0.36
Education categories			
Illiterate [a]	11034	0.02	0.15
Primary school [a]	11034	0.15	0.36
Middle school [a]	11034	0.36	0.48
High school [a]	11034	0.22	0.41
Technical school [a]	11034	0.13	0.33
University or higher [a]	11034	0.12	0.32
Activity levels			
Very light [a]	11034	0.26	0.44
Light [a]	11034	0.30	0.46
Moderate [a]	11034	0.30	0.46
Heavy [a]	11034	0.13	0.34
Very heavy [a]	11034	0.01	0.12
Medical insurance [a]	11034	0.66	0.47
Urban [a]	11034	0.51	0.50
Risk factors			
General obesity: BMI	11034	1.34	0.68
Central obesity: waist circumference [a]	8793	0.24	0.43
Smoking	11034	0.62	0.90
Heavy drinking [a]	11034	0.19	0.39
Working conditions			
Log (wage)	11034	5.92	1.09
Formal employment [a]	11034	0.72	0.45

Type of work unit			
Three-capital enterprise [a]	11034	0.01	0.10
Government [a]	11034	0.35	0.48
State service or institute [a]	11034	0.20	0.40
State-owned enterprise [a]	11034	0.14	0.35
Small collective enterprise [a]	11034	0.05	0.22
Large collective enterprise [a]	11034	0.08	0.27
Family contract farming [a]	11034	0.01	0.11
Private/individual enterprise [a]	11034	0.15	0.36
Family controls			
Log (household income adjusted to 2011)	11034	10.07	0.75
Household size	11034	3.84	1.32
Drinking water [a]	11034	0.94	0.24
Sanitation [a]	11034	0.58	0.49
Electricity [a]	11034	0.996	0.06
Health facilities (community level)			
Location of health facility [a]	11034	0.62	0.49
Distance to this health facility (km)	11034	0.90	3.47

Source: China Health and Nutrition Survey 1991, 1993, 1997, 2000, 2004, 2006, and 2009.

Note: The data for self-reported health status are from 1997 to 2006 and for waist circumference are from 1993 to 2009. The dependent variables are high blood pressure (a binary dummy: 1=yes, 0=no), self-reported health status (measured on a 4-point scale: 1=poor, 2=fair, 3=good, 4=excellent), daily sleep time, calorie/fat intake, time spent on food preparation and cooking, physical activity, and sedentary activity (watching TV, reading, writing, or drawing). BMI is measured on a 4-point scale (0=underweight, 1=normal weight, 2=overweight and 3=obese); waist circumference is a dichotomous variable. Smoking behavior is measured on a 4-point scale (based on number of cigarettes smoked, NCS): 0=nonsmoker, $1=1\leq NCS\leq 10$, $2=11\leq NCS\leq 20$, and $3=NCS>20$.The location of health facilities in the community is a dummy variable that equals 1 if a health facility is located in the village/neighborhood and 0 if in another village/town/city or in the respondent's city but in a different neighborhood.

[a] dummy variables.

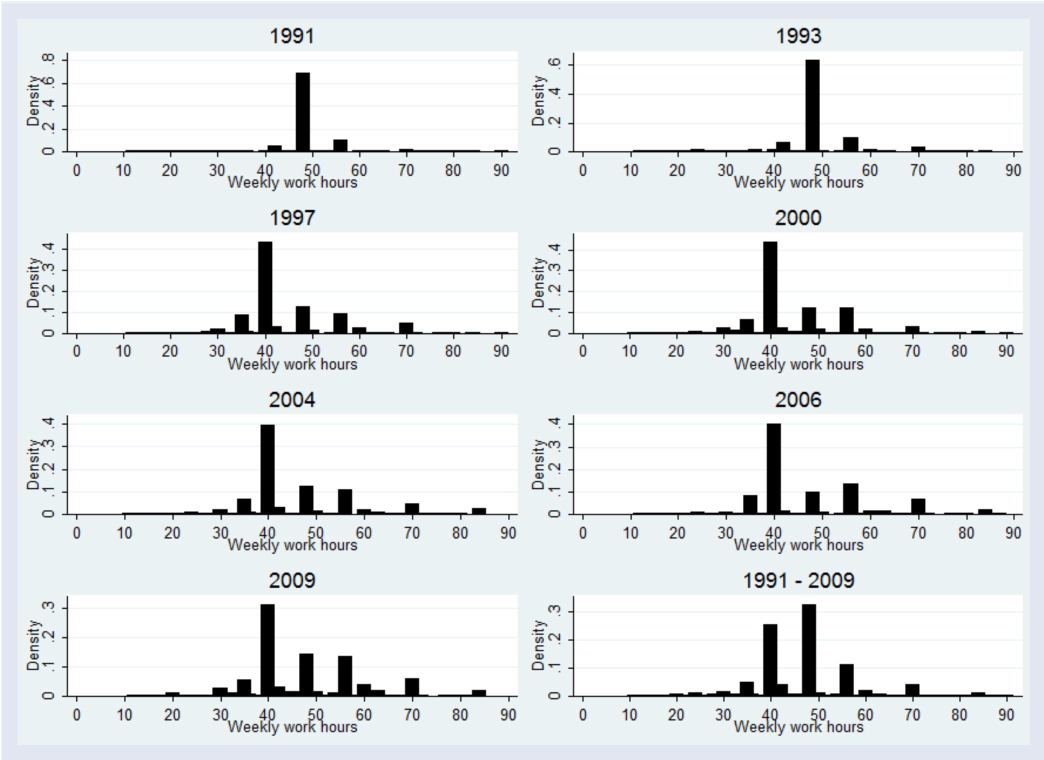

Figure A5.1 The distribution of weekly work hours: 1991-2009

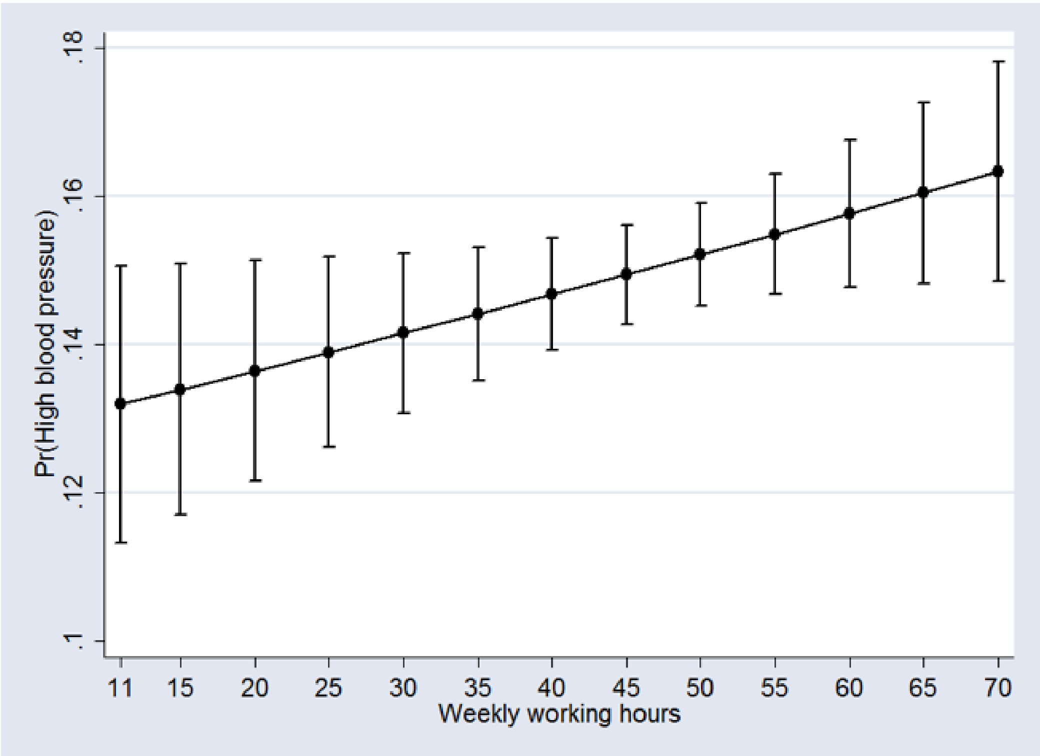

Figure A5.2 Marginal effects of weekly work hours on probability of high blood pressure

Table A5.2 Health measures from 1991 to 2009 (in percentage)

Health measures	All	1991	1993	1997	2000	2004	2006	2009
Self-reported health								
1=Poor	2.1	N.A	N.A	2.0	1.8	1.9	2.5	N.A
2=Fair	22.7	N.A	N.A	17.5	23.6	25.6	24.5	N.A
3=Good	56.3	N.A	N.A	65.1	52.6	54.1	52.2	N.A
4=Excellent	18.9	N.A	N.A	15.4	22.0	18.4	20.8	N.A
High blood pressure	15.1	11.2	12.5	15.1	17.7	17.9	14.0	19.3
Overweight and general obesity								
Overweight	26.5	20.3	24.4	27.0	29.4	30.9	29.1	31.6
General obesity	6.4	3.5	3.4	5.8	7.7	8.7	8.8	9.6
Abdominal obesity	24.3	N.A	12.9	19.8	24.8	29.5	29.5	31.7

Note: Self-reported health (1997-2006) is measured on a 4-point scale (1=poor, 2=fair, 3=good and 4=excellent). High blood pressure (1991-2009) is a binary variable (1=yes, 0=no). Based on the criteria of Working Group on Obesity in China (WGOC), overweight and general obesity (1991-2009) based on body mass index (BMI) are defined as 24≤BMI<28 and BMI ≥28 kg/m^2, respectively. Abdominal obesity (1993-2009) is defined as a waist circumference ≥85 cm for men and ≥80 cm for women. N.A denotes not available.

Table A5.3 OLS estimates of blood pressure: 1991–2009

Variables	Systolic blood pressure			Diastolic blood pressure		
	(1)	(2)	(3)	(4)	(5)	(6)
11≤WH≤30	-0.413			-0.282		
	(0.582)			(0.426)		
41≤WH≤50	0.305			0.129		
	(0.368)			(0.263)		
WH≥51	0.972**			0.594**		
	(0.405)			(0.293)		
WH		0.032***	0.013		0.017*	0.004
		(0.012)	(0.020)		(0.009)	(0.014)
N	11034	11034	6844	11034	11034	6844
Adj.R^2	0.268	0.268	0.271	0.238	0.238	0.242

Note: The dependent variable is continuous blood pressure (systolic blood pressure/diastolic blood pressure); WH = weekly work hours. Specifications (1) and (4) include work hour dummies (with 31≤WH≤40 as the reference); (2), (3), (5), and (6) include actual weekly work hours, with (3) and (6) regressed only on ≥41. All six specifications also include individual characteristics, risk behaviors (BMI, smoking, and heavy drinking), family characteristics, provincial dummies (with Liaoning as the reference), year dummies (with 1991 as the reference), and the characteristics of health facilities in the community. Robust standard errors are in parentheses;*p< 0.1, **p< 0.05, ***p< 0.01.

Curriculum Vitae

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Discussion Papers

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18/06/2014 – 21/06/2014 "The 28th Annual Conference of the European Society for Population Economics (ESPE)", the University of Minho, Braga, Portugal

07/05/2014 – 09/05/2014 "Conference on China after 35 Years of Economic Transition", London Metropolitan University, London, Britain

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Declaration of Authorship

Declaration in lieu of oath in accordance with § 8 paragraph 2 of the regulations for the degree "Doctor of Economics" at the University of Hohenheim.

1. I, Peng Nie, declare that this dissertation on "Essays on Health and Nutrition in China" and the work presented in it is my own and has been generated by me as the result of my own original research.

2. I have the approval of my co-authors to use the joint work in this dissertation and they endorse my individual contribution to the respective article.

3. I have used no sources or auxiliary means other than the ones acknowledged in this dissertation. I also have not used the illegal support of a third party, such as the help of a professional dissertation agency or consultancy. Where I have quoted from the work of others, the source is always given.

4. I affirm that the digital version submitted to the Faculty of Business, Economics and Social Sciences is identical to the hard copy.

5. I am aware of the meaning of this affirmation and the legal consequences of false or incomplete statements.

I hereby confirm the correctness of this declaration. I affirm in lieu of oath that I told the absolute truth and have not omitted any information.

Stuttgart, February 20th
Place, Date

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Signature