Social Science & Medicine 232 (2019) 58–76

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Family income and nutrition-related health: Evidence from food consumption in China

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ARTICLE INFO

Keywords:
Family income
Health
Food consumption
BMI
Overweight

ABSTRACT

With increasing family income, the prevalence of overweight has risen and become a serious threat to individual health and a major public health challenge in China. This study attempts to shed light on the mechanism of income impact on the adult health outcomes of BMI and overweight through five potential channels: nutritional intakes, dietary diversity, dietary knowledge, food preference, and dining out. Using the panel data from the China Health and Nutrition Survey (CHNS), we investigate the causal relationship between income and health by considering the changes in the minimum wage as a valid instrument to address the endogeneity problem of income in health estimation. The results indicate that rising income increases the adults' BMI and the propensity to be overweight; approximately 15.58% and 16.20% of income impact on BMI and overweight could be explained by the five channels considered, respectively. Among the five channels, dietary diversity plays the most significant role in explaining the income impact. We observe significant heterogeneity in income-BMI gradients across various income quantiles and subsamples. Specifically, income-BMI gradients tend to increase along with income percentiles, and income has a significantly positive impact on BMI and overweight for the male sample but it shows no significant impact for the female sample.

1. Introduction

With the rapid changes in urbanization, economic growth, technical change, and culture, remarkable changes in structures of diet and body composition have been indicated by extensive literature (Popkin and Ng, 2007), especially in low and middle income countries (Abdulai, 2010; Misra and Khurana, 2008; Popkin and Ng, 2007; Popkin, 2015; Popkin and Du, 2003). For instance, in the developing countries diets are shifting to more fats, more added caloric sweeteners, and more animal source foods (Popkin and Ng, 2007; Popkin and Du, 2003), as described by the process of nutritional transition (Popkin, 1993, 1999). Particularly, China has travelled along the path of economic transformation, and its remarkable progress has had important implications for income growth over the past four decades (Brandt et al., 2008). Rising income has bestowed many benefits on households in China and has facilitated poverty alleviation both regionally and nationally (Zhang and Donaldson, 2008). It has been indicated that consumers have experienced a remarkable nutrition improvement and a dramatic dietary change in China (Tian and Yu, 2015), and physical activity (Monda et al., 2007). This gives rise to the prevalence of nutrition related health issues in China, and it has been reported that approximately 39.2% of adults in China aged 18 and older are estimated to be overweight (Zhou et al., 2017). Such trends pose serious threats to individual health as they increase the risk of noncommunicable disease (Shimokawa, 2013; Tafreschi, 2015), and higher health costs not only for households but also for the entire nation. One available estimation by Popkin et al. (2006) shows the future health cost of the overweight epidemic (and the direct consequences thereof) will approach 9% of China's GDP by 2025.

It has been well documented that rising income is associated with certain negative health outcomes along the nutritional transition, such as higher rate of being overweight (Tafreschi, 2015; Bakkeli, 2016), while the mechanisms behind or the exact channels through which income affects individuals' body mass index (BMI) (calculated by

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https://doi.org/10.1016/j.socscimed.2019.04.016
Received 11 November 2018; Received in revised form 21 March 2019; Accepted 14 April 2019
Available online 25 April 2019
0277-9536/

weight in kilograms divided by the square of height in meters), and being overweight have been much less studied. A clear understanding of these channels has profound consequences not only for individuals to improve their health but also for policymakers to improve public health in China, as reducing income is not a rational option to reduce the rate of being overweight. It is also important to identify which channel is the most important one in transforming income growth into being overweight so that policymakers can focus on it when making policy changes in an effort to enable people to enjoy both higher living standards and better health.

The international literature has identified several factors that may be associated with both rising income and health outcomes of increasing BMI and prevalence of being overweight. One of the most important effects of income growth is the increase in the quantity of foods consumed, which could be measured by nutritional intakes. Generally, nutritional intakes assess the consumption of the three macronutrients: carbohydrate, fat, and protein (Mendez et al., 2005). It is a conventional belief that low nutritional intakes are a consequence of low income. However, the literature has not achieved a conclusive agreement on the extent to which income drives nutrient consumption. For instance, Skoufias et al. (2009) estimate income elasticity for various macro- and micronutrients in rural Mexico and find mixed results. They obtain positive income elasticities for fat but negative income elasticities for protein for the poorest households, while another study finds that in China, higher income tends to raise nutritional intakes of protein and fat but decrease intakes of carbohydrate in past decades (Huang and Gale, 2009). Thus, this concept must be reconsidered in the analysis of the channels through which income growth leads to increasing BMI and the propensity to be overweight.

Nutritional intakes, however, reveal limited information about diet quality and the associated health consequences (Doan, 2014). Investigating the consumption of calories or individual nutrients can provide only a partial understanding of the structural changes in diet quality and diet-related issues that accompany the nutrition transition. As a qualitative measure of food consumption, some studies have shown that dietary diversity can be used to reflect individuals' access to a wide variety of foods and is also a good proxy of the nutrient adequacy of the diet (Morseth et al., 2017; Torheim et al., 2004; Vandevijvere et al., 2010). The empirical literature on dietary diversity has been consistent in proving positive income effects on diet variety. For instance, Moon et al. (2002) find a positive linear income effect on diet diversity in Bulgaria, and another study finds similar results in Germany (Thiele and Weiss, 2003). A more recent study by Doan (2014) indicates a significant and positive income effect on dietary diversity in China from 2004 to 2009. Nevertheless, few studies have investigated whether dietary diversity serves as a channel through which income has an influence on adult health consequences.

In addition, dietary knowledge is another channel considered to transform rising income into increasing BMI and prevalence of overweight. We expect a strong link between family income and dietary knowledge because rising income gives individuals a greater possibility of obtaining more sources of information regarding nutrition and health, such as dietary knowledge (Clément and Bonnefond, 2015; Xie et al., 2003). Individuals with higher incomes are more likely to have access to the internet, podcasts, classes (Zhou et al., 2014), and mobile phones, and such access has been shown to significantly improve access to information and dietary quality (Sekabira and Qaim, 2017). Internationally, improving dietary knowledge has been shown to help people adjust their eating habits and exercise behavior in ways that keep them from becoming overweight (Bonaccio et al., 2013; Clément and Bonnefond 2015; Nayga, 2000; Wagner et al., 2016). As far as we can tell, no study has specifically investigated how income affects individuals' dietary knowledge, which in turn could affect individuals' health.

Food preference and dining out could also transfer income effect to nutrition-related health. With the development of the economy and increasing incomes, especially, in China, the food preference has been shifting away from high-carbohydrate food towards dense high-energy food (Batis et al., 2014; Clément and Bonnefond 2015; Curtis et al., 2007; Du et al., 2004); these changes might lead to prevalence of overweight. As one of the lifestyle changes, dining out has been indicated to have significant association with increasing income (French et al., 2010; Liu et al., 2015). These changes may also contribute to remarkable increase in BMI and being overweight since people who are regularly dining out, normally, have unhealthy consumption habit and less quality of the food (Machado-Rodrigues et al., 2018; Watts et al., 2017).

The overall goal of this study is to understand the relationship between rising income in China and the health outcomes of increasing BMI and prevalence of overweight to help policymakers formulate policies to address this rising public health concern. To achieve this goal, we have three specific objectives. First, we examine the impact of income on health by using minimum wage as a potential instrument to address the endogeneity of income in BMI and overweight estimation. Second, we seek to understand the income effect on the various channels—nutritional intakes, dietary diversity, dietary knowledge, food preference, and dining out. In this article, we focus solely on food consumption as the research perspective to detect how family income influences health through various aspects of food consumption. Finally, we illustrate how and to what extent income affects individuals' health through the potential channels considered by gradually decomposing the overall income effect on BMI and being overweight.

The existing literature on adult health relies mainly on the subjective measure of health by using binary or ordered categorical variables that fail to meet the requirements of heterogeneous income gradients. As BMI is continuous in nature, this paper also highlights the heterogeneous association between family income and adult health using unconditional quantile regression (Firpo et al., 2009) and a panel structure of the data. This type of econometric analysis helps identify which subgroups of adults are likely to improve or worsen their health when family income increases or decreases. Additionally, we also examine the possibility of heterogeneous income effect on male and female. The results of quantile regression show that in general, the income effect on health tends to increase from the lower quantile to the higher quantile; the results also demonstrate that family income contributes significantly to BMI and overweight for the male sample but is insignificant for the female samples.

In the next section, we introduce our econometric modelling approach. Section 3 briefly presents the data, and section 4 discusses the empirical results and accounts for the distribution of BMI. The last section concludes.

2. Econometric models

2.1. Benchmark model for the relationship between adult health and family income

To investigate the relationship between adult health and family income, we start with two benchmark models. As aforementioned, BMI is one of the most important indicators measuring an individual's health. It is estimated using the estimation strategy by Goode et al. (2014) as follows:

$$BMI_{it} = \alpha_0 + \beta_0 logM_{it} + \gamma \boldsymbol{X} + \varepsilon_{it} \tag{2.1}$$

where M_{it} is the family income inflated to 2011, and β_0 indicates the change in BMI when the income changes by 1%. $\boldsymbol{X}$ is a vector of control variables, including gender, *Hukou*, age, age squared, working status, education, marital status, and equivalent family size (Goode et al., 2014; Tafreschi, 2015). The vector $\boldsymbol{X}$ also includes the market prices of four main food commodities to control for the food market effect: pork, chicken, vegetables, and cereals (Shimokawa, 2013).

We employ an additional estimation for being overweight since its harmful effects have been widely documented. The regression follows a Probit model by using unbalanced panel data:

$$\Pr(Overweight_{it} = 1|\log M_{it}, \boldsymbol{X}) = \theta_0 + \theta_1 \log M_{it} + \boldsymbol{\delta X} + \varepsilon_{it} \quad (2.2)$$

where the dependent variable indicates whether an individual is overweight, and θ_1 represents the change in the probability of being overweight when the income changes by 1%. All control variables are the same as in Equation (2.1).

Considering the panel structure of our data, in our case where the key variables in channel variables do not vary much over time, fixed effect (FE) and first difference (FD) methods can therefore lead to imprecise estimates (Wooldridge, 2010: p. 326–334). In order to learn more about the population parameters, the models in Equations (2.1) and (2.2) are forced to be estimated using the random effects (RE) estimator. There is a significant assumption when using the RE estimator that income should not be correlated with any unobserved factors that may also influence the outcome variables. However, this assumption is rarely true in practice, which could lead to biased estimates. Following the method proposed by Mundlak (1978) and widely discussed and used by other researchers (Wooldridge, 2010; Sekabira and Qaim, 2017), we employ this method regarded as a pseudo-fixed-effects estimator as an additional comparison to the RE estimates. The main advantage of the Mundlak (1978) estimator is that it can control for bias that may arise from unobserved heterogeneity and omitted time-varying variables (Cameron and Trivedi, 2005; Wooldridge, 2010) when including covariate mean values as additional explanatory variables in the estimation; thus, the models in the following sections are always estimated with both the RE and the MK estimator.

When income is exogenous variable, β_0 in and θ_1 Equations (2.1) and (2.2) can be used to examine the income impact on BMI and overweight, respectively. However, the potential endogeneity of income may arise from unobserved heterogeneity and possible reverse causality (see also Chen et al., 2017). For instance, studies have indicated that BMI has a reverse effect on individual income (Cawley, 2004; Chen et al., 2017). Without considering the endogeneity of income in health estimation might cast doubt on the estimation results. Thus, we employ an instrumental variable (IV) estimation for BMI and overweight by using the minimum wage at the provincial level as an instrument for income. Generally, institutional changes could be used as potential valid instruments (Angrist and Krueger, 2001). Although, in the last decades, China has launched so many reforms and institutions that might have a direct effect on family income, few of them are applicable for both rural and urban households. For instance, Chen et al. (2017) use Rural Tax-for-Fee Reform as instrument for income in the estimation of children's health, while it only has a direct effect on income for these rural residents but it could hardly have a direct relation with the household living in urban areas.

Alternatively, the minimum wage is expected to serve as a valid instrument for income from two aspects. First, it tends to have a significantly direct impact on the family income not only for urban households but also for rural residents. Large proportions of rural laborers have shifted from agriculture to off-farm sectors including migration to the cities (Liu et al., 2017; Uchida et al., 2009; Wang et al., 2011; Zhao et al., 2018). Second, it is plausible to be an exogenous variable since the local governments have the considerable flexibility of setting up the minimum wage and it shows variation across provinces and over time (Haepp and Lin, 2017), so that the minimum wage should not directly affect the health of individuals.

In 1993, China issued the first minimum wage regulation and it was constituted into China's new version of the Labor Law in 1994. In 2004, the Ministry of Labor, China promulgated “The Minimum Wage Regulation (MWR)” with the following features. First, the local government should renew its minimum wage standards at least once every two years; second, minimum wage covers to employees in state-owned enterprises and private enterprises and also no full-time workers; third, a monthly minimum wage applied to full-time workers and an hourly minimum wage applied to part-time workers; fourth, penalty of violation of minimum wage regulation were quintupled. With these features, the MWR has covered a large number of working population no matter which types of work unit they are involved. Thus, we anticipate that the MWR tends to have a direct impact on household income and serves as a valid instrument for income in the health estimation.

To check the validity of our instrument, first, a Wald test of exogeneity is applied to test whether the variable is indeed endogenous. If the test is rejected, the estimates from the regular estimation will be biased. Under this circumstance, the IV estimation should be preferred, but when instruments are weak, point estimators will be biased and the Wald test is unreliable. Second, we use F-test and the Cragg-Donald Wald F statistic to test whether weak identification occurs in the instrument. As a rule of thumb, if *F-statistic* on the excluded instrument in the first stage is greater than 10, then one does not need to worry about the weak instrument problem (Andrews and Stock, 2005). When the instrument is weak, point estimators will be biased, and the Wald test is unreliable. Alternatively, the Anderson-Rubin (AR) test is well accepted if there is only one endogenous variable (Andrews and Stock, 2005), it is used to test if the parameters of the endogenous variables in the main equation are jointly significant. Third, to test the exclusion restriction condition of our instrument, we include the instrument in the health equation to check whether it has no significantly direct effect on the BMI. If the instrument is not statistically significant, we are reasonably convinced that the exclusion restriction condition is probably satisfied.

2.2. Decomposing the possible channels

The main goal of this study is to understand the channels through which income affects adult health. Based on the existing literature, the five potential channels regarding health and nutritional aspects are defined as nutritional intakes of carbohydrate, protein, and fat; dietary diversity; dietary knowledge; food preference; and dining out (Batis et al., 2014; Behrman and Deolalikar, 1988; Liu et al., 2015; Nayga, 2000; Philipson and Posner, 1999; Shimokawa, 2013; Strauss and Thomas, 1995; Zhou et al., 2017). We can then further measure to what extent these channels are associated with family income. The models are given as follows:

$$NI_{it} = \lambda_1 + \varphi_{1k} logM_{it} + \boldsymbol{\eta}_{1k}\boldsymbol{X} + \varepsilon_{1it} \quad (2.3)$$

$$DD_{it} = \lambda_2 + \varphi_2 logM_{it} + \boldsymbol{\eta}_2\boldsymbol{X} + \varepsilon_{2it} \quad (2.4)$$

$$DK_{it} = \lambda_3 + \varphi_3 logM_{it} + \boldsymbol{\eta}_3\boldsymbol{X} + \varepsilon_{3it} \quad (2.5)$$

$$FP_{it} = \lambda_4 + \varphi_4 logM_{it} + \boldsymbol{\eta}_4\boldsymbol{X} + \varepsilon_{4it} \quad (2.6)$$

$$DO_{it} = \lambda_5 + \varphi_5 logM_{it} + \boldsymbol{\eta}_5\boldsymbol{X} + \varepsilon_{5it} \quad (2.7)$$

where NI_{it}, DD_{it}, DK_{it}, FP_{it}, and DO_{it} denote nutritional intakes, dietary diversity, dietary knowledge, food preference, and dining out. Here, nutritional intakes (NI_{it}) consist of the three main components of carbohydrate, fat, and protein in the log form. Thus, in Equation (2.3), the subscripts of φ_{1k} , $k = 1, 2, 3$, represent the coefficients for carbohydrate, fat, and protein, respectively. The coefficient φ_{1k} indicates the change in the dependent variable when the income changes by 1%. Specifically, φ_{11}, φ_{12} , and φ_{13} indicate the percentage of the consumption of carbohydrate, fat, and protein, respectively, when the income changes by 1%. Dietary diversity (DD_{it}) is a qualitative measure of food consumption that reflects individuals' access to a wide variety of foods and is also a proxy of the nutrient adequacy of the diet. Dietary knowledge (DK_{it}) is and food preference (FP_{it}) are measured by a single index, respectively. Dining out (DO_{it}) is a continuous variable and indicates frequency of dining out within three days during the survey period. In Equations (2.4)–(2.7), the coefficients of $logM_{it}$ ($\varphi_2, \varphi_3, \varphi_4, \varphi_5$) indicate the changes in dietary diversity, dietary knowledge, food preference, and dining out, respectively, when the income changes by 1%. All control variables are identical to those in equation (2.1).

After identifying a significant correlation between these potential channels and family income, the role of nutritional intakes, NI_{it}, is used as an example to illustrate the decomposing process of the income effect on adult health. The nutritional intakes NI_{it} are introduced into our benchmark model as shown below:

$$BMI_{it} = \alpha_1 + \beta_1 logM_{it} + \rho_1 NI_{it} + \partial_1 \boldsymbol{X} + \mu_{1it} \tag{2.8}$$

When the coefficient of family income in (2.6) is significantly changed compared with its coefficient in benchmark model (2.1), we can distinguish that the overall income effect on adult health expressed in Equation (2.7) can be decomposed by the correlation for family income and nutritional intakes (NI_{it}) multiplied by the correlation between adult health and nutritional intakes (NI_{it}) and added to the unexplained income effect, which affects adult health but not through the current channel of nutritional intakes.

$$\beta_0 = \beta_1 + \rho_1 \frac{cov(logM_{it}, NI_{it})}{var(logM_{it})} + \frac{cov(logM_{it}, \mu_{1it})}{var(logM_{it})} \tag{2.9}$$

Thus, $\beta_0 - \beta_1 = \rho_1 * \varphi_1 + \frac{cov(logM_{it}, \mu_{1it})}{var(logM_{it})}$. As with the strategy for nutritional intakes, NI_{it}, we decompose the other possible channels by using the estimated coefficients from the models below:

$$BMI_{it} = \alpha_2 + \beta_2 logM_{it} + \rho_2 DD_{it} + \partial_2 \boldsymbol{X} + \mu_{2it} \tag{2.10}$$

$$BMI_{it} = \alpha_3 + \beta_3 logM_{it} + \rho_3 DK_{it} + \partial_3 \boldsymbol{X} + \mu_{3it} \tag{2.11}$$

$$BMI_{it} = \alpha_4 + \beta_4 logM_{it} + \rho_4 NI_{it} + \rho_4 DD_{it} + \partial_4 \boldsymbol{X} + \mu_{4it} \tag{2.12}$$

Next, we introduce all five channels into the model (2.1):

$$BMI_{it} = \alpha' + \beta' logM_{it} + \rho_1' NI_{it} + \rho_2' DD_{it} + \rho_3' DK_{it} + \rho_4' FP_{it} + \rho_5' DO_{it} + \partial \boldsymbol{X} + \mu_{it} \tag{2.13}$$

The difference in coefficients of income in models (2.1) and (2.13) can be used to identify how and to what extent income passes through these five potential channels to affect adult health. β' is the unexplained effect of income on health, which might also pass through other unobservable channels in this study. From the perspective of food consumption, increasing income might increase the quantities of nutritional intakes and frequency of dining out, might lead to higher scores in dietary diversity and healthier food preference, and might increase the possibility of obtaining dietary knowledge, all of which influence consumption behavior accordingly. As aforementioned, it should be noted that income might influence adult health through other important channels, such as medical treatment, which are beyond the scope of this study.

In accordance with the decomposition methodology for BMI, we conduct similar estimations for overweight to examine how and to what extent income affects the likelihood of an adult being overweight through these five-suspected channels. As discussed before, the endogeneity of income needs to be considered for BMI and overweight estimations, and thus we follow the same strategy and use minimum wage as an instrumental variable for income.

2.3. Heterogeneity of the correlation between income and health

The existing literature mainly focuses on the mean effect of income on health, while potential heterogeneity in the relationship between health and family income has been increasingly highlighted (Bonnefond and Clément, 2014; Dai et al., 2014; Goode et al., 2014; Lei et al., 2014; Liu et al., 2014). Since BMI is a continuous health measure, the unconditional quantile regression developed by Firpo et al. (2009) is employed to estimate the heterogeneous income effect for adults at various levels of BMI. As stated by Firpo et al. (2009), the unconditional quantile regression can be directly applied to evaluate the economic impact of changing the distribution of independent variables on quantiles of the unconditional distribution of the dependent variable. The estimation of the heterogeneous relationship between family income and adult health can help identify which subgroups of adults are likely to be most sensitive to increases in family income. These groups would benefit most from governmental income-support policies such as subsidies.

The influence function from the unconditional quantile regression has been broadly used to check the robustness of the estimation. For each quantile, the influence function $\mathrm{IF}(\mathrm{Y}, q_\tau)$ is known to be $(\tau - \mathrm{I}(Y_{it} \le q_\tau))/f_Y(q_\tau)$, where $\hat{q}_\tau$ is the τ^{th} quantile of Y, I is an indicator function, and f_Y is the density of the marginal distribution of Y. By adding the influence function back into the distributional statistics, the recentered influence function (RIF) is obtained by $q_\tau + \mathrm{IF}(\mathrm{Y}, q_\tau)$. The RIF for quantiles amounts to a linear approximation of the nonlinear quantile function and captures the change of quantiles in response to a change in the underlying distribution (Firpo et al., 2009). In our study, the dependent variable is BMI. We model $\mathrm{RIF}(BMI_{it}, q_\tau)$ as a function of family income and covariates:

$$\mathrm{E}[\mathrm{RIF}(BMI_{it}, q_\tau)|\mathrm{logM}_{it}, \boldsymbol{X}] = \vartheta_{0\tau} + \vartheta_\tau logM_{it} + \boldsymbol{\omega X} \tag{2.14}$$

The dependent variable in the regression is $\mathrm{RIF}(BMI_{it}, q_\tau) = q_\tau + \tau - I(BMI_{it} \le q_\tau)/f_{BMI}(q_\tau)$, while $\mathrm{RIF}(BMI_{it}, q_\tau)$ is unobservable in practice. Thus, all unknown components are replaced with sample estimators in the following function:

$$\hat{\mathrm{RIF}}(BMI_{it}, \hat{q}_\tau) = \hat{q}_\tau + (\tau - I(BMI_{it} \le \hat{q}_\tau))/\hat{f}_{BMI}(\hat{q}_\tau) \tag{2.15}$$

The computation is performed by estimating the sample quantile $\hat{q}_\tau$ and estimating the density function $\hat{f}_{BMI}(\hat{q}_\tau)$ at that point of $\hat{q}_\tau$ using kernel methods. From there, a dummy variable, $I(BMI_{it} \le \hat{q}_\tau)$, is generated, which indicates whether the value of BMI is below q_τ. Finally, we can simply estimate model (2.12) by running an RE model on the estimated dependent variable of the covariates. By applying this method, we can readily recover the average partial effect of a small location shift of the log of family income on the unconditional τ-quantile of BMI.

3. Data

The dataset used for this study is from the China Health and Nutrition Survey (CHNS), which is an international collaborative project between the National Institute of Nutrition and Food Safety at China Centers for Disease Control and Prevention and the Carolina Population Center, University of North Carolina at Chapel Hill. The CHNS is longitudinal and includes nine waves of 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011, consissting of 9 provinces (Heilongjiang, Liaoning, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, Guizhou) and 3 autonomous cities (Beijing, Shanghai, Chongqing); it comprises questions about the target households, their members, and their communities. The protocols used during each of the waves remain as similar as possible.

3.1. Samples

To fulfil the objectives of this study, three criteria are applied to restrict our sample from the CHNS. First, the CHNS survey team started to collect information on dietary knowledge only from 2004 onwards. Thus, our analysis uses data only from the 2004 and later waves. Second, the respondents to questions on dietary knowledge belonged to age cohorts over 12 years old. To make our results comparable to other studies on adult health, we restrict the sample to those aged 18–65 at the time of the survey; children and the elderly outside this range are excluded. Third, BMI threshold does not apply to minors and the elderly, pregnant women, and adults suffering from chronic disease; therefore, these individuals are excluded. After these exclusions, 14,655 individuals (30,971 observations) with full information remain in the

Table 1
Descriptive statistics of selected the key variables.
Source: Author's calculation using the CHNS data (2004–2011).

Variables	Definition	All	Male	Female	Difference	Urban	Rural	Difference
		(1)	(2)	(3)	(2)–(3)	(4)	(5)	(4)–(5)
Dependent Variables								
BMI	Body mass index (kg/m^2)	23.40	23.45	23.36	0.09*	23.70	23.18	0.52***
		(3.30)	(3.23)	(3.36)		(3.28)	(3.30)	
Overweight	1 = If BMI ≥ 24; 0 = Otherwise	0.40	0.41	0.39	0.02**	0.44	0.37	0.07***
		(0.49)	(0.49)	(0.49)		(0.50)	(0.48)	
Independent Variables								
LogM	Natural logarithm of per capita family income (Yuan) inflated to 2011	8.72	8.74	8.70	0.04*	9.08	8.44	0.64***
		(1.97)	(1.98)	(1.95)		(1.93)	(1.95)	
Nutritional Intakes (NI):								
Log (Carbohydrate)	Natural logarithm of 3-Days Ave: Carbohydrate (g)	5.62	5.70	5.55	0.15***	5.51	5.70	−0.19***
		(0.37)	(0.36)	(0.37)		(0.36)	(0.36)	
Log (Fat)	Natural logarithm of 3-Days Ave: Fat (g)	4.16	4.22	4.09	0.13***	4.25	4.09	0.17***
		(0.54)	(0.53)	(0.54)		(0.50)	(0.56)	
Log (Protein)	Natural logarithm of 3-Days Ave: Protein (g)	4.14	4.22	4.07	0.15***	4.18	4.12	0.06***
		(0.33)	(0.32)	(0.33)		(0.33)	(0.33)	
Dietary Diversity (DD)	Individual dietary diversity score	8.75	8.72	8.78	−0.5*	9.59	8.13	1.46***
		(2.07)	(2.03)	(2.11)		(1.77)	(2.06)	
Dietary Knowledge (DK)	Dietary knowledge index	6.28	6.28	6.29	−0.01	6.91	5.81	1.10***
		(3.63)	(3.62)	(3.64)		(3.51)	(3.64)	
Food Preference (FP)	Food preference index	0.17	0.12	0.22	0.09*	0.24	0.12	1.12***
		(1.00)	(1.01)	(0.97)		(1.00)	(1.00)	
Dining Out (DO)	Frequency of Dining out within 3-Days	0.58	0.64	0.52	0.12***	0.83	0.39	0.44***
		(1.05)	(1.09)	(1.01)		(1.21)	(0.86)	
Gender	1 = Male; 0 = Female	0.48				0.49	0.47	0.019**
		(0.50)				(0.50)	(0.50)	
Hukou[a]	1 = Urban; 0 = Rural	0.43	0.44	0.42	0.02**			
		(0.49)	(0.50)	(0.49)				
Age	Years	45.33	45.28	45.38	−0.09	45.58	45.15	0.43**
		(11.71)	(11.92)	(11.51)		(11.72)	(11.70)	
Working status	1 = Yes; 0 = No	0.68	0.77	0.60	0.17***	0.59	0.75	−0.16***
		(0.47)	(0.42)	(0.49)		(0.49)	(0.43)	
Physical	6 = No working ability (Under age 7); 5 = Very heavy; 4 = Heavy; 3 = Moderate; 2 = Light; 1 = Very light	2.66	2.78	2.55	0.24***	1.87	3.25	1.38***
		(1.22)	(1.21)	(1.22)		(0.96)	(1.05)	
Education	6 = Master or above; 5 = College or university; 4 = Vocational education; 3 = High school; 2 = Junior high school; 1 = Elementary school; 0 = Illiterate	1.88	2.08	1.700	0.38***	2.47	1.45	1.02***
		(1.15)	(1.06)	(1.20)		(1.08)	(0.99)	
Marital status	1 = Married with companion; 0 = Unmarried or married without companion	0.88	0.86	0.89	−0.02***	0.86	0.89	0.03***
		(0.33)	(0.34)	(0.32)		(0.35)	(0.31)	
Family size[b]	Household members	2.57	2.57	2.58	−0.01	2.32	2.76	−0.44***
		(0.82)	(0.81)	(0.83)		(0.70)	(0.85)	
Chicken	Price of chicken at community level (Yuan/Jin[c])	19.26	19.28	19.25	0.03	18.73	19.66	−0.93***
		(6.94)	(6.94)	(6.95)		(6.46)	(7.26)	
Pork	Price of pork at community level (Yuan/Jin[c])	24.32	24.29	24.35	−0.06	23.95	24.60	−0.65***
		(6.41)	(6.39)	(6.43)		(6.20)	(6.55)	
Vegetables	Price of vegetables at community level (Yuan/Jin[c])	2.69	2.68	2.70	−0.02	2.75	2.65	0.10***
		(0.96)	(0.96)	(0.97)		(0.99)	(0.95)	
Cereals	Price of cereals at community level (Yuan/Jin[c])	4.54	4.55	4.54	0.01	4.56	4.53	0.03*
		(1.17)	(1.16)	(1.17)		(1.18)	(1.15)	
Observations		30971	14764	16207		13242	17729	
No. of individuals		14655	7060	7595		7612	7966	

[a] The Hukou system started with the 1958 People's Republic of China Hukou Registration Regulation, in which each citizen was classified in an agricultural or nonagricultural Hukou, commonly referred to as rural or urban Hukou.

[b] The first adult in the household has a weight of 1. Each additional adult aged 14 and over has a weight of 0.5. Each child aged under 14 has a weight of 0.3. c. 1 Jin = 0.5 kg.

final estimations.

3.2. Variables

Table 1 presents the summary statistics of the major dependent and independent variables tabulated by the characteristics of gender and *Hukou* registration. In this study, two dependent variables measuring health are BMI and overweight status. The CHNS survey team conducted measures of height and weight, which were used to calculate BMI. The average BMI is 23.40 kg/m^2, and it tends to increase along the survey year and varies across gender and *Hukou* registration, showing higher values for the male and urban samples than for the female and rural samples as shown in Fig. 1.

The distribution of BMI density is shown in Fig. 2; On the basis of the standard for Asian people proposed by the World Health Organization (WHO, 2000) that individuals whose BMI equals 24 or above are defined as overweight, approximately 40% of the 18-65-year-olds in our sample are observed to be overweight. In terms of various subsamples, this number is approximately 2% higher for males than for females and 7% higher for those in urban areas than for those in rural areas at the statistically significant level. Given the large population of China, overweight rates calculated by this method translate to more

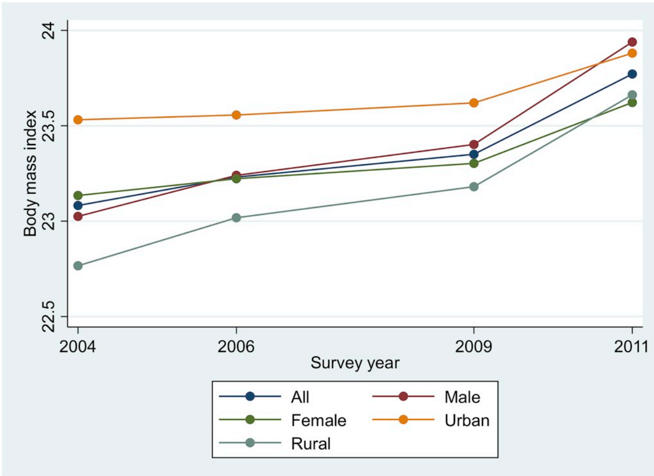

Fig. 1. 2004–2011 average body mass index (BMI) changes by gender and Residence.
Source: CHNS 2004, 2006, 2009, and 2011

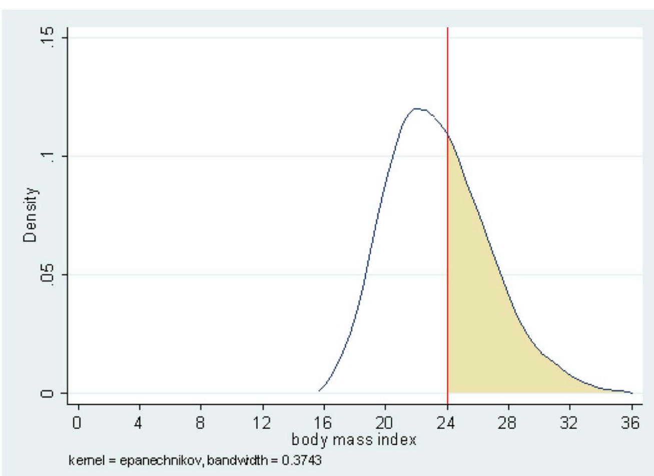

Fig. 2. Distribution of body mass index (BMI).
Note: BMI equals 24 or above are defined as overweight.
Source: CHNS 2004, 2006, 2009, and 2011

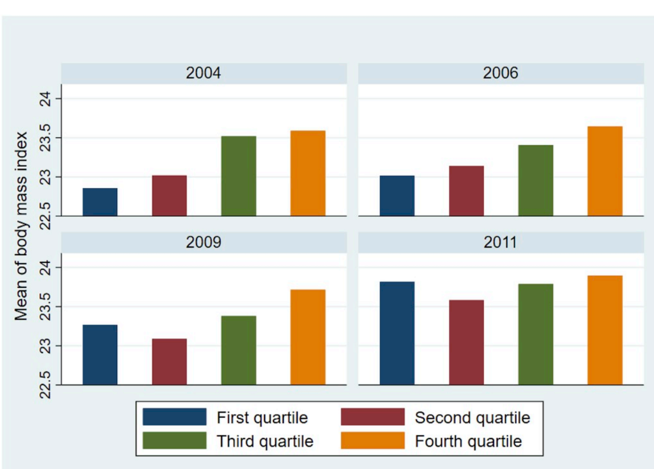

Fig. 3. Average BMI cross Income Quartiles and over Survey Years.
Source: CHNS 2004, 2006, 2009, and 2011

than five hundred million adults with the condition. Moreover, Fig. 3 indicates an increasing tendency of BMI cross income quartiles and over survey years.

Moreover, the CHNS collected information about food consumption, dietary diversity, and dietary knowledge, encompassing over 1500 food items consumed at home or elsewhere. To ensure the data quality, the CHNS enumerators recorded food consumption during a period of three consecutive days, randomly selected from Monday to Sunday, and the measurements were spread over the whole week. Moreover, the CHNS team used this information, along with information on the nutritional contents of these food items provided by the Chinese Food Nutrition Table (Yang et al., 2002), to calculate the 3-days average intake of the three macronutrients, carbohydrate (g), fat (g), and protein (g), at the individual level. The descriptive statistics show that the three components of nutritional intakes are comparable to those used in other studies, though the standard deviations are larger (Shimokawa, 2013). Males and those living in rural areas have a higher caloric (kcal) intake on average, but their components are different. Those in rural areas consume less protein and fat but more carbohydrate.

Following Kennedy et al. (2011), a dietary diversity score is calculated for 14 food groups, including cereals, vitamin A-rich vegetables and tubers, white tubers, dark green leafy vegetables, other vegetables, Vitamin A-rich fruits, other fruits, organ meat (iron rich), flesh meat, eggs, fish, legumes (nuts and seeds), milk and milk products, oils and fats. It takes the value of 1 when an individual consumes a specific food group and 0 otherwise. In this way, the maximum dietary diversity score is 14 when an individual consumed all 14 food groups during the survey period. A higher score suggests a higher propensity to consume more food groups and a greater likelihood of meeting micronutrient needs. On average, the individual dietary diversity score is 8.72 and shows significant differences for various subsamples. Female and urban samples tend to have higher dietary diversity than male and rural samples (Table 1).

As aforementioned, since 2004, the CHNS has started to pay attention to dietary knowledge for each individual over 12 years old. Respondents finished a twelve-item quiz on basic dietary knowledge, as presented in Table A1. For each question, the respondents chose 'agree,' 'disagree,' or 'unknown.' Based on the criteria in WHO (1998), we generate an indicator that takes the value of 1 for a correct answer, −1 for an incorrect answer, and 0 for 'unknown' and construct a summary index of these answers (Shimokawa, 2013). The higher the score is, the greater the knowledge of nutritional intakes. The results show a large variation of dietary knowledge between those in urban and rural areas, but the dietary knowledge index is statistically insignificant by gender.

Food preference is generated from five questions concerning consumption of fast food, salty snack foods, fruits, vegetables, soft drinks and sugared fruit drinks. For each question, the respondents are asked to report their preference, like or dislike this specific food. We take the value of 1 for liking a healthy preference, −1 for liking an unhealthy preference, and 0 for 'neutral' and calculate a summary index of these answers as for dietary knowledge. A higher score indicates a healthier food consumption preference. The details regarding these questions are presented in Table A2.

The independent variable of interest is the logarithm form of household per capita income inflated to the 2011 price level. As discussed before, income might be endogenous in the health estimation, and the IV estimation should be employed by using the minimum wage regulation as an instrument. The data for minimum wage of each province is compiled according to the relevant data of the "Human Resources and Social Security Network" of each province, as show in Table A3. The changes in minimum wage in the surveyed provinces and municipality are presented in Fig. 4. Generally, during the survey period from 2004 to 2011, the minimum wage shows an increasing tendency in all surveyed regions and this pattern is in correspondence with the family income.

Furthermore, the CHNS survey also includes information on a wide

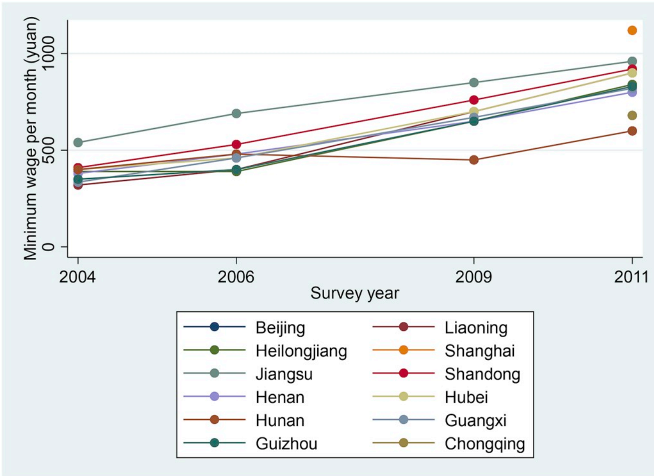

Fig. 4. 2004–2011 minimum wage regulations in the surveyed provinces and municipality.
Source: The minimum wage data of each province is compiled according to the relevant data of the "Human Resources and Social Security Network" of each province.

number of variables, covering individual and family characteristics such as age, marital status, educational attainment, employment record, and equivalent family size, as aforementioned (Table 1). Other control variables are the logarithm of prices at the community level for four food groups, cereal, pork, chicken, and vegetables, at the 2011 price level.

3.3. Correlations between family income and adult health

This section examines how the adult health indicators of BMI and the percentage of overweight vary at different family income levels. Table 2 presents correlations between BMI and percentage of overweight and the quartile of family income. Both BMI and percentage of being overweight show increasing tendencies along income quartiles, ranging from 23.10 to 35.62% for the first quartile to 23.78 and 44.97% for the fourth quartile; the same pattern can be observed for all subsamples. Overall, we conclude that a significantly positive correlation exists between BMI (overweight) and income. For subsamples, male and rural samples show consistent growth but female and urban samples tend to increase until third quartile and then decrease slightly at the fourth quartiles.

4. Empirical results

All models are estimated with an RE panel and a pseudo-fixed-effects estimator. The RE estimator assumes that $logM_{it}$ is uncorrelated with any unobserved factors that may also influence the outcome variables. However, as individuals self-select into income variation activities, this assumption may be violated, which could lead to biased estimates. Therefore, in addition to the RE estimates, we also use a pseudo-fixed-effects estimator, as proposed by (Mundlak, 1978). The MK estimator includes covariate mean values as additional explanatory variables, thus controlling for bias that may arise from time-invariant unobserved heterogeneity (Cameron and Trivedi, 2005). In the rest of the study, we rely on MK estimation to interpret more plausible results.

4.1. Adult health and family income gradient

Following model (2.1) and (2.2), the estimation results are presented in Table 3, respectively. Similar to (Tafreschi, 2015), we find that family income has a significantly positive impact on BMI and overweight from regular RE and MK estimators, as well as from the IV estimations using both RE and MK estimators. The evidence the endogeneity test shows that income indeed is endogenous variable in both BMI and overweight estimation, as the null hypothesis that income is exogenous is rejected at the conventional level of significance. F-statistics are larger than 10, suggesting that all IV estimation has no weak instruments problem. Similar results can be found from the Cragg-Donald Wald F statistic and AR Statistics. We also find the minimum wage has no significant and direct effect on the health outcome, suggesting that the exclusion restriction condition of our instrument is probably satisfied. Thus, the following discussion will solely rest on the IV estimation from MK estimator.

In the view of BMI, the MK estimation results show that one percent increase in family income is associated with an average BMI increase of 0.374. Considering that the cutoff for being overweight is a BMI of 24, this means that when family income doubles, a large proportion of adults face the risk of becoming overweight. The IV Probit estimation results from the MK estimator also indicate a significant impact of family income on the probability of being overweight for the whole sample (Table 3); given other variables unchanged, the marginal effect of family income suggests that one percent of family income increase will increase the predicted probability of being overweight by approximately 16.2%. In addition, we also find there exists gender-specific effect; males tend to have larger BMI and higher likelihood to be overweight.

4.2. Decomposition of the possible channels

The decomposition approach in this study requires estimations of the univariate relationships between channel variables and family income (Blanden et al., 2007). Specifically, to understand which channels are likely to affect BMI and being overweight is to review which of them has a relationship with family income; without this link, they cannot play a role in our explanation.

Table 4 provides the IV estimation results of the impacts of family income on potential channels, following econometric models (2.3)–(2.7), as a comparison, Table A4 presents the impact of income on the five channels without addressing the edogeneity of family income.

Table 2
Descriptive statistics of BMI and overweight cross various income quartiles and their correlations.
Source: Author's calculation using the CHNS data (2004–2011).

		All		Male		Female		Urban		Rural	
		BMI	Overweight	BMI	Overweight	BMI	Overweight	BMI	Overweight	BMI	Overweight
Income quartile	First	23.10	35.62%	22.90	33.13%	23.27	37.73%	23.45	40.73%	22.98	34.16%
	Second	23.19	37.33%	23.09	35.83%	23.29	38.87%	23.80	45.38%	22.96	34.21%
	Third	23.54	41.82%	23.70	44.08%	23.42	40.32%	23.78	45.47%	23.21	37.00%
	Fourth	23.78	44.97%	24.13	50.37%	23.44	39.47%	23.78	44.92%	23.56	41.85%
Corr (LogM, BMI)		0.058*		0.116**		0.003		0.044		0.033	
Corr (LogM, Overweight)		0.021**		0.043***		0.001		0.019*		0.009	

Notes: *p < 0.10, **p < 0.05, ***p < 0.010.

Table 3
IV estimation of the impact of income on BMI and overweight.

Estimation method	BMI				Overweight			
	RE	MK	IV-RE	IV-MK	RE	MK	IV-RE	IV-MK
Second stage:								
LogM	0.022***	0.013***	0.580***	0.374*	0.007**	0.004	0.230***	0.162**
	(0.01)	(0.00)	(0.17)	(0.23)	(0.00)	(0.00)	(0.05)	(0.08)
Gender	0.241***	0.392***	0.317***	0.441***	0.094***	0.128***	0.122***	0.146***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.03)	(0.03)	(0.03)	(0.03)
Hukou	0.142***	−0.075*	−0.015	−0.105**	0.066***	−0.019	0.002	−0.063*
	(0.05)	(0.04)	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)	(0.03)
Age	0.257***	0.256***	0.297***	0.216***	0.074***	0.080***	0.089***	0.074***
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Age^2	−0.002***	−0.002***	−0.003***	−0.002***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Working status	−0.082*	−0.027	−0.408***	−0.188*	−0.050***	−0.024	−0.192***	−0.118**
	(0.05)	(0.05)	(0.11)	(0.11)	(0.02)	(0.02)	(0.04)	(0.05)
Physical	−0.084***	−0.033	−0.041**	−0.039*	−0.031***	−0.011	−0.013**	−0.001
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Education	−0.003	−0.023	−0.138***	−0.035	0.001	0.000	−0.052***	−0.032
	(0.03)	(0.02)	(0.04)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Marital status	0.228***	0.065	0.128	−0.005	0.067**	0.006	0.026	−0.025
	(0.08)	(0.07)	(0.10)	(0.11)	(0.03)	(0.04)	(0.04)	(0.05)
Family size	0.020	0.071**	0.081*	0.114**	−0.001	0.021*	0.027**	0.046**
	(0.04)	(0.03)	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)	(0.02)
Chicken	−0.023***	−0.008	−0.017**	−0.011*	−0.011***	−0.003**	−0.007***	−0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Pork	0.024***	0.013***	0.020***	0.012***	0.009***	0.004***	0.007***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Vegetables	0.016	−0.024	−0.057	−0.024	0.002	−0.015	−0.028*	−0.022
	(0.04)	(0.03)	(0.05)	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)
Cereals	0.015	0.032	−0.043	0.029	−0.003	0.004	−0.024*	0.001
	(0.03)	(0.03)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Mundlak mean values		Y		Y		Y		Y
First stage:								
Logminiwage			1.094***	1.013***			1.094***	1.013***
			(0.07)	(0.10)			(0.07)	(0.10)
R^2			0.0972	0.0434			0.0972	0.0434
F-Statistics			244.32	244.51			244.32	244.51
Cragg-Donald Wald F statistic			244.317	244.509			244.317	244.509
Stock-Yogo weak ID test critical value			16.38	16.38			16.38	16.38
AR-Statistics(P-value)			23.56 (0.00)	11.88 (0.00)			24.05 (0.00)	14.05 (0.00)
Endogeneity test *P-value*			0.0000	0.0001			0.0000	0.0001
Observations	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655

Note: Coefficients for BMI are presented with standard errors in parentheses. Marginal effects for overweight are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. RE refers to random-effects estimator, and MK refers to Mundlak estimator; IV-RE refers to random-effects estimator with instrument, and IV-MK refers to Mundlak estimator with instrument.
Source: Author's estimation using the CHNS data (2004–2011).
*$p < 0.10$, **$p < 0.05$, ***$p < 0.010$.

They are conditional on other control variables, as those in the regression of health and family income gradient. The endogeneity test shows that income indeed is endogenous variable in the five channel variables, as the null hypothesis that income is exogenous is rejected at the conventional level of significance, and evidence from F-test and Cragg-Donald Wald F statistic suggest that all IV estimation has no weak instruments problem. Thus, the IV estimation from MK estimator is preferred and interpreted in the following.

With the exception of carbohydrate in which income shows a significantly negative impact, the variables in the measures of nutritional intakes are positively related to family income, which is similar to the findings of Huang and Gale (2009). Specifically, with a 1% income increase, the quantities of fat and protein increase by 0.12% and 0.11% according to the results from the MK estimator. Our results indicate that wealthier adults are more likely to consume more fat and protein, although the coefficients for fat is not significant. The results also reveal that higher-income individuals tend to have a higher dietary diversity score and more dietary knowledge, while income seems have no significant effect on food preference and dining out.

To detect to what extent these channels affect adult health through family income, we employ models (2.10)–(2.13). The five channel variables are introduced into the model gradually, and the estimation results for BMI and overweight are presented in Tables 5 and 6, respectively.

Regarding the effects of the five potential channels on BMI, as presented in Table 5, it is apparent that they all have a significant effect on BMI, no matter whether the RE or the MK estimator is used (as a comparison, the estimations from the regular RE and MK estimation are presented in Table A5 without addressing the endogeneity of family income). The endogeneity test and weak instrument test are qualified at the conventional level, indicating the IV estimation using MK estimator is preferred. Thus, we solely focus on the interpretation of results from the IV estimation using the MK estimator. Specifically, carbohydrate consumption tends to decrease adults' BMI, while protein is a strong predictor of BMI. One percentage increase in protein consumption is associated with an approximately 0.161 increase in BMI as shown in

Table 4
IV estimation of the impact of income on nutritional intakes, dietary diversity, and dietary knowledge.

Dependent Variable	Nutritional Intakes (NI)						Dietary Diversity (DD)		Dietary Knowledge (DK)		Food Preference (FP)		Dining Out (DO)	
	Log (Carbohydrate)		Log (Fat)		Log (Protein)									
	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK
Second stage:														
LogM	−0.170**	−0.225**	0.111*	0.118	0.074	0.107*	1.328***	1.387***	6.651***	4.315***	0.014	−0.024	0.330**	0.389
	(0.08)	(0.11)	(0.06)	(0.09)	(0.05)	(0.06)	(0.22)	(0.35)	(0.65)	(0.55)	(0.07)	(0.08)	(0.16)	(0.24)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Mundlak mean values		Y		Y		Y		Y		Y		Y		Y
First stage:														
Logminiwage	1.094***	1.013***	1.094***	1.013***	1.094***	1.013***	1.094***	1.013***	1.094***	1.013***	1.094***	1.013***	1.094***	1.013***
	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)
R^2	0.0078	0.0053	0.0078	0.0053	0.0078	0.0053	0.0078	0.0053	0.0078	0.0053	0.0078	0.0053	0.0078	0.0053
F-Statistics	244.32	210.51	244.32	210.51	244.32	210.51	244.32	210.51	244.32	210.51	244.32	210.51	244.32	210.51
Cragg-Donald Wald F statistic	244.317	210.509	244.317	210.509	244.317	210.509	244.317	210.509	244.317	210.509	244.317	210.509	244.317	210.509
Stock-Yogo weak ID test critical value	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38
AR-Statistics	0.84	2.66	216.57	236.49	795.75	761.82	132.02	142.49	246.53	251.43	4.80	4.76	132.29	106.85
(P-value)	(0.35)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)
Endogeneity test *P-value*	0.5007	0.1701	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0276	0.0287	0.0000	0.0000
Observations	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655

Notes: Coefficients are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. IV-RE refers to random-effects estimator with instrument, and IV-MK refers to Mundlak estimator with instrument.
Source: Author's estimation using the CHNS data (2004–2011).
*p < 0.10, **p < 0.05, ***p < 0.010.

Table 5
IV estimation of possible mechanisms underlying the impact of income on BMI.
Source: Author's estimation using the CHNS data (2004–2011).

Estimation Method	IV-RE								IV-MK							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Second stage:																
LogM	0.5798***	0.5523***	0.5361***	0.5235***	0.5799***	0.5764***	0.5231***	0.4728***	0.3742**	0.3485**	0.3462*	0.3557**	0.3742**	0.3728**	0.3322*	0.3159*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.17)
Nutritional Intakes (NI):																
Log (Carbohydrate)		−0.1388**-*					−0.1106**	−0.1085*		−0.0886*					−0.0676	−0.0647
		(0.05)					(0.06)	(0.06)		(0.05)					(0.05)	(0.05)
Log (Fat)		0.0010					−0.0103	−0.0109		0.0020					−0.0071	−0.0075
		(0.03)					(0.03)	(0.03)		(0.03)					(0.03)	(0.03)
Log (Protein)		0.2000***					0.1497**	0.1508**		0.1611***					0.1215*	0.1212*
		(0.07)					(0.07)	(0.07)		(0.06)					(0.06)	(0.06)
Dietary Diversity (DD)			0.0342***				0.0289***	0.0283***			0.0280***				0.0236***	0.0232***
			(0.01)				(0.01)	(0.01)			(0.01)				(0.01)	(0.01)
Dietary Knowledge (DK)				0.0072*				0.0065				0.0066				0.0061
				(0.00)				(0.00)				(0.00)				(0.00)
Food Preference (FP)					−0.0085			−0.0092					−0.0138			−0.0143
					(0.01)			(0.01)					(0.01)			(0.01)
Dining Out (DO)						0.0134		0.0018						0.0099		0.0017
						(0.01)		(0.01)						(0.01)		(0.01)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values[a]									Y	Y	Y	Y	Y	Y	Y	Y
First stage:																
Logminiwage	1.094***	0.0914**	1.011***	1.065***	1.094***	1.060***	0.091***	0.88***	1.030***	0.863 ***	0.947***	1.003***	1.030***	1.002***	0.855***	0.828***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
R^2	0.0972	0.1028	0.1068	0.0978	0.0972	0.9564	0.1088	0.1097	0.1016	0.1065	0.1102	0.1021	0.1016	0.1029	0.1120	0.1127
F-Statistics	244.32	165.40	209.94	229.97	244.37	228.89	165.59	153.57	210.51	143.42	178.86	198.38	210.52	198.83	141.68	131.84
Cragg-Donald Wald F statistic	244.317	165.401	209.941	229.966	244.368	228.890	165.587	153.570	210.509	143.425	178.855	198.381	210.521	198.831	141.675	131.838
Stock-Yogo weak ID test critical value	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38
AR-Statistics (P-value)	23.56 (0.00)	9.62 (0.00)	21.05 (0.00)	18.10 (0.00)	23.41 (0.00)	23.58 (0.00)	9.60 (0.00)	6.79 (0.01)	11.88 (0.00)	3.41 (0.06)	10.33 (0.00)	8.17 (0.00)	11.73 (0.00)	11.89 (0.00)	3.39 (0.66)	1.76 (0.18)
Endogeneity test _P-value_	0.0000	0.0021	0.0000	0.0000	0.0000	0.0000	0.0000	0.0095	0.0007	0.0652	0.0005	0.0049	0.0008	0.0007	0.0654	0.1814
Observations	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655

Note: Coefficients are presented with standard errors in parentheses. Standard errors are cluster-corrected at county level. IV-RE refers to random-effects estimator with instrument, and IV-MK refers to Mundlak estimator with instrument.

*p < 0.10, **p < 0.05, ***p < 0.010.

[a] Mundlak mean values include mean values of other control variables except gender.

Table 6
IV estimation of possible mechanisms underlying the impact of income on overweight.
Source: Author's estimation using the CHNS data (2004–2011).

Estimation Method	IV-RE								IV-MK							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Second stage:																
LogM	0.2300***	0.2184***	0.2115***	0.2100***	0.2300***	0.2287***	0.2081***	0.1895***	0.1685***	0.1559***	0.1540***	0.1599***	0.1686***	0.1674***	0.1489***	0.1412**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Nutritional Intakes (NI):																
Log (Carbohydrate)		−0.0357*					−0.0248	−0.0248		−0.0213					−0.0128	−0.0121
		(0.02)					(0.02)	(0.02)		(0.02)					(0.02)	(0.02)
Log (Fat)		0.0020					−0.0025	−0.0027		0.0023					−0.0013	−0.0013
		(0.01)					(0.01)	(0.01)		(0.01)					(0.01)	(0.01)
Log (Protein)		0.1114***					0.0935***	0.0944***		0.0974***					0.0829***	0.0829***
		(0.03)					(0.03)	(0.03)		(0.03)					(0.03)	(0.03)
Dietary Diversity (DD)			0.0141***				0.0102***	0.0101***			0.0120***				0.0085**	0.0084**
			(0.00)				(0.00)	(0.00)			(0.00)				(0.00)	(0.01)
Dietary Knowledge (DK)				0.0026*				0.0025				0.0024				0.0023
				(0.00)				(0.00)				(0.00)				(0.00)
Food Preference (FP)					−0.0046			−0.0049					−0.0066			−0.0068
					(0.01)			(0.01)					(0.00)			(0.01)
Dining Out (DO)						0.0040		−0.0006						0.0034		−0.0001
						(0.01)		(0.01)						(0.01)		(0.01)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values[a]									Y	Y	Y	Y	Y	Y	Y	Y
First stage:																
Logminiwage	1.094***	0.914***	1.011***	1.065***	1.094***	1.060***	0.912***	1.094***	1.030***	0.863***	0.947***	1.003***	1.030***	1.002***	0.855***	0.828***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
R^2	0.0972	0.1028	0.1068	0.0978	0.0972	0.0988	0.1088	0.1097	0.1016	0.1065	0.1102	0.1021	0.1016	0.1029	0.1120	0.1127
F-Statistics	244.32	165.40	209.94	229.97	244.37	228.89	165.59	153.57	210.51	143.42	178.86	198.38	210.52	198.83	141.68	131.84
Cragg-Donald Wald F statistic	244.317	165.401	209.941	229.966	244.368	228.890	165.587	153.570	210.509	143.425	178.855	198.381	210.521	198.831	141.675	131.838
Stock-Yogo weak ID test critical value	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38
AR-Statistics (P-value)	24.05 (0.00)	10.83 (0.00)	21.39 (0.00)	19.39 (0.00)	23.82 (0.00)	23.95 (0.00)	10.8 (0.00)	8.25 (0.00)	14.05 (0.00)	5.12 (0.02)	11.22 (0.00)	10.62 (0.00)	13.85 (0.00)	14.00 (0.00)	5.08 (0.02)	3.34 (0.07)
Endogeneity test *P-value*	0.0000	0.0011	0.0000	0.0000	0.0000	0.0000	0.0011	0.0042	0.0002	0.0652	0.005	0.0013	0.002	0.0002	0.0240	0.0666
Observations	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655

Note: Marginal effects are presented with standard errors in parentheses. Standard errors are cluster-corrected at county level. IV-RE refers to random-effects estimator with instrument, and IV-MK refers to Mundlak estimator with instrument.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.010$.
[a] Mundlak mean values include mean values of other control variables except gender.

column (10). Dietary diversity shows a positive association with BMI, and a one-point increase in dietary diversity could drive an increase in BMI of 0.028, as shown in column (11). However, our suspected channel of the dietary knowledge index, food preference, and dining out have no statistically significant impact on BMI, as shown in column (10).

The coefficient of income across different model specifications from the MK estimator shown in Table 5, columns (9)–(16), indicates that nutritional intakes, dietary diversity, dietary knowledge, food preference, and dining out can explain 0.0257 points (6.87%), 0.028 points (7.48%), 0.0185 points (4.94%), 0.000 points (0.00%), and 0.0014 points (0.37%) of the coefficient of income in the BMI estimation. After controlling for both nutritional intake and dietary diversity in column (15), we find that the coefficients of these variables change slightly compared with column (10), but the significance levels remain unchanged except the coefficient for Carbohydrate that turns to insignificant. These changes might be due to the effect of dietary diversity on nutritional intakes since a significant correlation exists between dietary diversity and nutritional intakes (Shimokawa, 2013; Zhou et al., 2017). A similar explanation can be applied for coefficient changes in dietary diversity and nutritional intakes when introducing dietary knowledge into the estimation, as shown in column (12). In total, the amount of the income effect on BMI from these five channels is approximately 15.58%.

In the estimates for overweight based upon IV estimation using MK estimator, all potential channels are highly correlated with being overweight, as shown in Table 6 (the estimations from the regular RE and MK estimation are presented in Table A6 without addressing the endogeneity of family income). The endogeneity test and F-test are qualified at the conventional level; this suggests the IV estimation using MK estimator is preferred. When only the nutritional intakes are introduced in column (8), fat and protein are likely to increase the probability of being overweight, although the coefficient of fat is not significant. In contrast, carbohydrate tends to decrease the likelihood of being overweight. This finding may suggest that a shift in the Chinese diet from cereals to animal products would give rise to a greater prevalence of overweight in China (Batis et al., 2014; Du et al., 2004).

Surprisingly, a significantly positive effect of dietary diversity on overweight is shown in column (9), which implies that individuals with higher dietary diversity are more likely to be overweight. It is widely accepted that higher dietary diversity is associated with a healthy, nutritionally adequate diet and could reduce the risk of major chronic diseases (Mozaffarian and Ludwig, 2010), while evidence from recent studies also indicate that higher dietary diversity score is associated with higher probability of being obesity (Karimbeiki et al., 2018). The possible reason might be that greater dietary diversity is along with suboptimal eating patterns, for instance, higher intakes of processed foods, refined grains, and sugar-sweetened beverages and lower intakes of minimally processed foods such as fish, fruits, and vegetables (de Oliveira Otto et al., 2018).

Dietary knowledge has a positive impact on overweight but it is not significant. When gradually controlling nutritional intakes and dietary knowledge, as in column (10) and (15), we find that the coefficients of these variables change slightly. Similar to the explanation for BMI, these changes might be due to the correlations among the five channels.

The coefficient of income in estimations for overweight from the MK estimator, as presented on the right side of Table 6, shows that nutritional intakes and dietary diversity may explain an identical amount (0.0126 and 0.0145) of the income coefficient, accounting for 7.4% and 8.6% of the total income effect on overweight, as shown in columns (10) and (11), respectively. However, income could barely affect overweight through dietary knowledge, food preference, and dining out, as the coefficient of income changes slightly in column (12), (13), (14) compared with column (9). With the inclusion of nutritional intake and dietary diversity in column (15), the total amount accounts for an increase of 11.63%. When including all the transmission variables, approximately 16.20% of the income effect on overweight could be explained through the channels studied.

4.3. Heterogeneity of the income impact on health

To check for heterogeneity of the income gradient on adult health for various income percentiles, we apply the unconditional quantile regression using the panel data, as specified in the model (2.13). The six various percentiles (the 5th, 25th, 45th, 60^{th}, 75th, and 90^{th} percentiles) of the BMI distribution are estimated as adults under the 5th percentile are malnourished, above the 60^{th} percentile are overweight, and above the 90^{th} percentile are obese. This approach allows us to easily examine the income effect on health at various amounts of nutrition, and the family income is instrumented by the minimum wage. The estimation results are presented in Table 7.

The results indicate that significant heterogeneity exists in the income effect on adult health at various levels of the BMI distribution. Substantial differences in the income effect on adult health across various sample specifications are also observed. The results from row (1) in Table 7, without including the five channel variables, show that the effect of income on adult health is positive and tends to increase along the various income percentiles (see also Asiseh and Yao, 2016). This finding implies that when height remains constant, adults with a higher BMI will gain more weight with each increase in family income. Similar results can also be found in the literature that income has positive effect on BMI, using the data from the CHNS (Du et al., 2004; Lu and Goldman, 2010; Xiao et al., 2013). Although existing literature has highlighted that there might exist an inverted U-shape relationship between family income and BMI, as well as the likelihood of being overweight in developing economies (Dinsa et al., 2012; McLaren, 2007; Sobal and Stunkard, 1989), it might not be the case in our study for China. Having not directly introduced a nonlinear relation between income and body weight, Tafreschi (2015) investigate the interaction term between income and development index covering the period from 1991 to 2009 from the CHNS. Tafreschi (2015) also draws the conclusion that the income gradient of individual body weight to changes sign from positive to negative in the process of comparatively rapid economic development. Similarly, Asiseh and Yao (2016) also find that BMI first increases with family income at decreasing rate and then decreases (see also Ren et al., 2018). However, most of the existing literature using the CHNS data does not control for the individual fixed effect and the endogeneity problem of income; without this consideration the results might be biased in these studies (Asiseh and Yao, 2016; Ren et al., 2018; Tafreschi, 2015).

The other possible explanation for our results could be that family income of the majority of households is still under the turning point of the reverse effect. For instance, one recent study by Clément (2017) applies a semiparametric analysis and instrumental estimation to investigate the income and BMI gradient among Chinese urban adults. They find that negative effect of income on BMI is only observed for female sample; for male samples income and BMI gradient is still close to low-income countries, showing a positive sign but negative sign been only observed at top 1% of income distribution. According to their estimation for the urban sample, the critical point of income for the inverted U-ship is around 30,166 CNY for the urban residents during 2004–2011, while a similar estimation can be found in another study by Ren et al. (2018), with a critical value of income at 25,595 CNY for the pooled sample. Ren et al. (2018) also indicate that proximately 95.8% of observations in their sample are below this threshold; therefore, the marginal effect of income is still showing the positive sign. In addition, most of studies are using the data before 2011; this might not be proper to illustrate the nutritional transition of China nowadays. As family income has been consistently increased during past years after 2011, more research is essential to collect the latest data and examine the current nutritional transition procedure of China; this would be likely to observe the reversal income effect distinctly.

Table 7
IV estimation of unconditional quantile regressions for the impact of income on BMI.
Source: Author's estimation using the CHNS data (2004–2011).

Variables		All	Q5	Q25	Q45	Q60	Q75	Q90
LogM	(1)	0.374**	0.104	0.454	0.716***	0.677**	0.815*	1.110***
		(0.18)	(0.23)	(0.28)	(0.25)	(0.32)	(0.44)	(0.39)
LogM	(2)	0.316*	0.043	0.259	0.569***	0.562*	0.702*	0.999***
		(0.17)	(0.25)	(0.25)	(0.22)	(0.29)	(0.40)	(0.37)
Other control variables		Y	Y	Y	Y	Y	Y	Y
Mundlak mean values[a]		Y	Y	Y	Y	Y	Y	Y

Note: Coefficients are presented with standard errors in parentheses. Standard error are cluster-corrected at province level.
Row (1) includes the control variables and Mundlak mean values from Table 3; Row (2) also includes all channel variables, control variables and Mundlak mean values in Table 5; Observations under q5 are malnourished, above q60 are overweight, and above q90 are obese, respectively.
*p < 0.10, **p < 0.05, ***p < 0.010.
[a] Mundlak mean values include mean values of other control variables except gender.

However, there is no significant relationship between income and BMI at the lowest tail of income distribution. Therefore, any policy designed to improve the health of malnourished adults, especially those below the 5th percentile, must consider vigorously increasing their income. The health benefits of family income seem to be realized only when income increases to a certain level; otherwise, this benefit will be discounted. After controlling for all five channels in the row (2) in Table 7, the magnitude of the family income estimates decreases but the significance remains; this implies that the five channels considered indeed play a significant role in transmitting the income effect on BMI.

To examine the heterogeneity of income effect for different gender, we conduct the estimations for the male and female sample, respectively. The instrumental variable estimation results are presented in Table 8, and regular OLS and Probit estimations for BMI and

Table 8
IV estimation of the impact of family income on BMI and overweight by gender when controlling for all channel variables.
Source: Author's estimation using the CHNS data (2004–2011).

Subsample	BMI				Overweight			
	Male		Female		Male		Female	
	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK	IV-RE	IV-MK
Second stage:								
LogM	0.717***	0.264	0.399**	0.447	0.282***	0.160*	0.157**	0.159
	(0.19)	(0.22)	(0.19)	(0.31)	(0.07)	(0.10)	(0.07)	(0.10)
Nutritional Intakes (NI):								
Log (Carbohydrate)	−0.101	−0.069	−0.037	−0.016	−0.009	−0.003	−0.009	−0.005
	(0.07)	(0.06)	(0.07)	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)
Log (Fat)	−0.021	−0.006	−0.025	−0.026	0.005	0.010	−0.016	−0.017
	(0.04)	(0.03)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Log (Protein)	0.006	0.060	0.001	−0.008	0.033	0.047	0.035	0.034
	(0.10)	(0.09)	(0.10)	(0.09)	(0.03)	(0.04)	(0.05)	(0.05)
Dietary Diversity (DD)	−0.019*	0.005	−0.003	−0.007	−0.007	−0.001	−0.004	−0.004
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Dietary Knowledge (DK)	0.017**	0.012	−0.000	−0.000	0.005**	0.003	0.002	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Food Preference (FP)	0.004	0.000	−0.024	−0.030*	−0.004	−0.005	−0.007	−0.009
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Dining Out (DO)	−0.009	0.008	−0.037*	−0.030	−0.001	0.004	−0.023***	−0.019***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values[a]		Y		Y		Y		Y
First stage:								
Logminiwage	0.869***	0.797***	0.892***	0.853***	0.869***	0.800***	0.892***	0.853***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
R^2	0.1165	0.1200	0.1066	0.1099	0.1165	0.1200	0.1066	0.1099
F-Statistics	69.30	56.82	84.01	74.65	69.30	56.82	84.01	74.65
Cragg-Donald Wald F statistic	69.300	56.820	84.012	74.650	69.300	56.820	84.012	74.650
Stock-Yogo weak ID test critical value	16.38	16.38	16.38	16.38	16.38	16.38	16.38	16.38
AR-Statistics(P-value)	1.29 (0.26)	0.00 (0.96)	4.64 (0.03)	1.84 (0.18)	4.08 (0.04)	1.25 (0.26)	2.90 (0.09)	1.02 (0.31)
Endogeneity test *P-value*	0.2670	0.9670	0.0222	0.1486	0.0441	0.2537	0.0760	0.2839
Observations	14764	14764	16207	16207	14764	14764	16207	16207
No. of individuals	7060	7060	7595	7595	7060	7060	7595	7595

Notes: Coefficients for BMI are presented with standard errors in parentheses. Marginal effects for overweight are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. IV-RE refers to random-effects estimator with instrument, and IV-MK refers to Mundlak estimator with instrument.
*p < 0.10, **p < 0.05, ***p < 0.010.
[a] Mundlak mean values include mean values of other control variables except gender.

overweight are presented in Table A7. In the view of estimations for BMI, evidence from F exclusion test and Cragg-Donald Wald F statistic suggests that we have no weak instrument problem, while there is not sufficient information in the male sample to reject the null that income is endogenous in BMI estimation, so a regular MK regression as shown in Table A5 may be appropriate. Thus, we conclude that income has a significantly positive impact on males' BMI but it has no impact on females' BMI. Similarly, evidence from the estimations for overweight shows that rising income tends to increase the likelihood of being overweight for the male sample (see also Bakkeli, 2016), while Clément (2017) finds that for males whose income at the top 1% of income distribution income shows a negative effect. However, no significant impact of income on overweight is observed for the female sample. This result reflects the fact that income has reached a saturation to have influence on females' BMI, and non-economic reason might play stronger role for the females such as health consciousness and concern about physical appearance (Bonnefond and Clément, 2014). More future studies are required to explore non-economics reasons explaining the female's BMI and overweight.

In conclusion, significant heterogeneity across various income quantiles and subsamples is revealed. Specifically, the income-BMI gradient tends to increase along the income percentiles, and males witness significant income effects on their BMI and being overweight while this impact tends to be insignificant for female samples.

5. Conclusion

With the substantial increase in family income, the prevalence of overweight has risen and has become a serious threat to individual health and a major public health challenge in the transitional economy of China. After using minimum wage as a valid instrument to address the potential endogeneity of income in health estimation, this study attempts to shed light on the impact of family income on the adult health outcomes of BMI and overweight through the potential channels of nutritional intakes, dietary diversity, dietary knowledge, food preference, and dining out. The data is drawn from the CHNS covering the periods of 2004, 2006, 2009, and 2011.

The estimation results show that family income has a significant impact on the potential channels considered except food preference and dining out. Precisely, an increase in family income improves the nutritional components of protein and fat intakes but is negatively correlated with carbohydrate intake. This finding is consistent with the findings of other studies that people from higher-income families are more likely to have more calorie intake through protein and fat from meat and milk products and less from carbohydrate from cereal foods (Huang and Gale, 2009; Ogundari and Abdulai, 2013). People with higher incomes are likely to consume a greater diversity of foods. As expected, income is also significantly positively correlated with dietary knowledge since adults are more conscious of health and have greater access to health information with increasing income (Binkley, 2010; Clément and Bonnefond 2015; Sekabira and Qaim, 2017).

To investigate the causal relation of income on health, we perform estimations for BMI and overweight. The results indicate that, family income still has a significantly positive impact on BMI and being overweight in transitional economy of China. To further illustrate the channels through which family income might affect adult health, the suspected channels are gradually introduced to examine the changes in the coefficient of family income. Overall, these five channels could explain approximately 15.58% and 16.20% of the total income effect on BMI and being overweight, respectively, from a pseudo-fixed-effects estimator. In particular, dietary diversity is the most important factor among the five channels as the coefficient of family income changes to the greatest extent; it contributes approximately 7.48% and 8.6% of the total income effect on BMI and overweight, respectively. However, it should be noted that an unexplained income effect might affect adult health through other channels that are not considered in our empirical model due to the data constraints. To some extent, this study provides a first example for future research on investigating the mechanism of income effect on adult health through other channels.

To check the heterogeneity of the income effect on adult health, we conduct unconditional quantile estimations across different sample specifications for gender and for the various income percentiles. In the same vein as nutritional transition in developing economies, the results from quantile regressions for BMI show that income effect on health increases consistently from the lower percentile to the higher percentile but always shows a positive sign, implying that BMI tends to increase with income growth and increases at a rising rate along income percentiles. For the subsamples, family income has a significant contribution to BMI and overweight for the male subsample but it has no impact for the female sample.

Our estimation results indicate two profound policy implications. First, income is still one of the important factors affecting adult health and nutrition in the transitional economy of China. Unlike in developed countries, where higher income classes are less likely to have unhealthy food consumption and health-related problems (Binkley, 2010), rising family income in China not only tends to increase the nutritional intakes of protein but also results in a dramatic prevalence of health issues from overnutrition. Second, family income could significantly promote adults' dietary diversity and dietary knowledge, but these channels might not be an efficient way to address adult health issues, as these channels have an unexpectedly positive effect on BMI and being overweight. Shimokawa (2013) indicates that dietary knowledge alone largely affects the quantity and quality of food consumed among overweight and non-overweight adults, respectively. As suggested by Nayga (2000), the most effective method of health education might need to highlight the disease element of poor dietary habits and health.

Funding

This research uses data from the China Health and Nutrition Survey (CHNS). We thank the National Institute for Nutrition and Health, China Center for Disease Control and Prevention, Carolina Population Center (P2C HD050924, T32 HD007168), the University of North Carolina at Chapel Hill, the NIH (R01HD30880, DK056350, R24 HD050924, and R01-HD38700) and the NIH Fogarty International Center (D43 TW009077, D43 TW007709) for financial support for the CHNS data collection and analysis files from 1989 to 2015 and future surveys, and the China-Japan Friendship Hospital, Ministry of Health for support for CHNS 2009, Chinese National Human Genome Center at Shanghai since 2009, and Beijing Municipal Center for Disease Prevention and Control since 2011. The authors acknowledge funding support provided by National Natural Science Foundation of China of China (71673008; 71742002). We also thank all participants of the Food and Health Economics Workshop at the Toulouse School of Economics (TSE) June 7 and 8, 2018 for their useful comments on an earlier draft of this article.

Appendix

Table A1
Questions concerning dietary knowledge in the CHNS.

Dietary knowledge:	
Do you strongly agree, somewhat agree, neutral, somewhat disagree or strongly disagree with this statement?	True/False
**Please note that the question is not asking about your actual habits.*	
Q1: Choosing a diet with a lot of fresh fruit and vegetables is good for one's health	T
Q2: Eating a lot of sugar is good for one's health	F
Q3: Eating a variety of foods is good for one's health	T
Q4: Choosing a diet high in fat is good for one's health	F
Q5: Choosing a diet with a lot of staple foods (rice and rice products and wheat and wheat products) is not good for one's health	T
Q6: Consuming a lot of animal products daily (fish, poultry, egg and lean meat) is good for one's health	F
Q7: Reducing the amount of fatty meat and animal fat in the diet is good for one's health	T
Q8: Consuming milk and dairy products is good for one's health	T
Q9: Consuming beans and bean products is good for one's health	T
Q10: Physical activities are good for one's health	T
Q11: Sweaty sports or other intense physical activities are not good for one's health	T
Q12: The heavier one's body is, the healthier he or she is	F
Index rules: "1" point was given for a correct answer, "-1" point for an incorrect answer, and "0" points for the other answers.	

Source: The dietary knowledge questionnaire is from the official website of China Health and Nutrition. Survey (http://www.cpc.unc.edu/projects/china).

Table A2
Questions concerning food preference in the CHNS.

Food Preference:	Healthy (H)/Unhealthy (U)
How much do you like this food: Like very much, like somewhat, neutral, dislike somewhat, or dislike very much?	
Q1: Fast food (KFC, pizza, hamburgers, etc.)	U
Q2: Salty snack foods (potato chips, pretzels, French fries, etc.)	U
Q3: Fruits	H
Q4: Vegetables	H
Q5: Soft drinks and sugared fruit drinks	U
Index rules: "1" point was given for liking a healthy preference, "-1" point for liking an unhealthy preference, and "0" points for neutral.	

Source: The dietary knowledge questionnaire is from the official website of China Health and Nutrition. Survey (http://www.cpc.unc.edu/projects/china).

Table A3
Descriptive statistics of minimum wages in each province.

Miniwage (Yuan/month)	2004	2006	2009	2011	Mean (S.D)[a]
Beijing	465	580	800	960	701.25 (221.52)
Liaoning	320	400	700	900	580 (268.82)
Heilongjiang	390	390	650	840	567.5 (219.15)
Shanghai	570	690	960	1120	835 (250.40)
Jiangsu	540	690	850	960	760 (183.85)
Shandong	410	530	760	920	655 (228.69)
Henan	380	480	650	800	577.5 (185.54)
Hubei	400	460	700	900	615 (230.00)
Hunan	400	480	450	600	482.5 (85.00)
Guangxi	335	460	670	820	571.25 (215.88)
Guizhou	350	400	650	830	557.5 (224.11)
Chongqing	320	400	680	680	520 (187.62)
Mean (S.D.)[b]	406.67 (81.08)	496.67 (106.80)	710 (125.70)	860.83 (135.14)	618.54 (211.09)

Note: a. Line a presents the mean value and standard deviation of minimum wage in each province (2004–2011). b. Row b presents the mean value and standard deviation of minimum wage of twelve provinces in each survey year.
Source: The minimum wage data of each province is compiled according to the relevant data of the "Human Resources and Social Security Network" of each province.

Table A4
The impact of income on nutritional intakes, dietary diversity, and dietary knowledge

Dependent Variable	Nutritional Intakes (NI)						Dietary Diversity (DD)		Dietary Knowledge (DK)		Food preference (FP)		Dining Out (DO)	
	Log (Carbohydrate)		Log (Fat)		Log (Protein)									
	RE	MK	RE	MK	RE	MK	RE	MK	RE	MK	RE	MK	RE	MK
LogM	−0.001	0.000	0.013**	0.011**	0.011***	0.010***	0.106***	0.090***	0.114***	0.047***	0.001	0.001	0.021***	0.016***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Mundlak mean values		Y		Y		Y		Y		Y		Y		Y
Observations	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655	14655

Note: Coefficients are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. RE refers to random-effects estimator, and MK refers to Mundlak estimator.
Source: Author's estimation using the CHNS data (2004–2011).
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.010$.

Table A5
Possible mechanisms underlying the effects of family income on BMI.

Estimation Method	RE							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LogM	0.0218***	0.0200***	0.0189***	0.0198***	0.0218***	0.0215***	0.0181***	0.0167***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Nutritional Intakes (NI):								
Log (Carbohydrate)		−0.1915***					−0.1534**	−0.1354**
		(0.07)					(0.07)	(0.06)
Log (Fat)		0.0084					−0.0061	−0.0089
		(0.03)					(0.03)	(0.03)
Log (Protein)		0.2358**					0.1717*	0.1685*
		(0.10)					(0.09)	(0.09)
Dietary Diversity (DD)			0.0423***				0.0356**	0.0319**
			(0.02)				(0.02)	(0.01)
Dietary Knowledge (DK)				0.0210***				0.0186***
				(0.01)				(0.01)
Food preference (FP)					−0.0084			−0.0092
					(0.01)			(0.01)
Dining Out (DO)						0.0199		0.0039
						(0.02)		(0.02)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values [a]								
Observations	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655
Estimation Method	MK							
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
LogM	0.0133***	0.0125***	0.0119**	0.0133***	0.0134***	0.0133***	0.0115**	0.0115**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nutritional Intakes (NI):								
Log (Carbohydrate)		−0.1040**					−0.0817*	−0.0775*
		(0.05)					(0.05)	(0.05)
Log (Fat)		0.0027					−0.0067	−0.0072
		(0.03)					(0.03)	(0.03)
Log (Protein)		0.1716**					0.1306*	0.1300*
		(0.08)					(0.07)	(0.07)
Dietary Diversity (DD)			0.0290**				0.0242*	0.0237*
			(0.01)				(0.01)	(0.01)
Dietary Knowledge (DK)				0.0083				0.0075
				(0.01)				(0.01)
Food preference (FP)					−0.0139*			−0.0145*
					(0.01)			(0.01)
Dining Out (DO)						0.0105		0.0017
						(0.02)		(0.01)

Other control variables	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values [a]	Y	Y	Y	Y	Y	Y	Y	Y
Observations	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655

Notes: Coefficients are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. RE refers to random-effects estimator, and MK refers to Mundlak estimator.
Source: Author's estimation using the CHNS data (2004–2011).
*p < 0.10, **p < 0.05, ***p < 0.010.
[a] Mundlak mean values include mean values of other control variables except gender.

Table A6
Possible mechanisms underlying the effect of family income on overweight.

Estimation Method	RE							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LogM	0.0073**	0.0062*	0.0059*	0.0064*	0.0073**	0.0072**	0.0054*	0.0048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nutritional Intakes (NI):								
Log (Carbohydrate)		−0.0624*					−0.0465	−0.0392
		(0.03)					(0.03)	(0.03)
Log (Fat)		0.0031					−0.0028	−0.0033
		(0.01)					(0.01)	(0.01)
Log (Protein)		0.1318***					0.1072***	0.1054***
		(0.04)					(0.04)	(0.04)
Dietary Diversity (DD)			0.0179***				0.0134**	0.0118**
			(0.01)				−0.0033	(0.01)
Dietary Knowledge (DK)				0.0087***				0.0078***
				(0.00)				(0.00)
Food preference (FP)					−0.0047			−0.0049
					(0.00)			(0.00)
Dining Out (DO)						0.0079		0.0009
						(0.01)		(0.01)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values [a]								
Observations	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655
Estimation Method	MK							
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
LogM	0.0041	0.0034	0.0033	0.0040	0.0041	0.0041	0.0030	0.0030
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nutritional Intakes (NI):								
Log (Carbohydrate)		−0.0326					−0.0230	−0.0211
		(0.03)					(0.03)	(0.02)
Log (Fat)		0.0020					−0.0019	−0.0019
		(0.01)					(0.01)	(0.01)
Log (Protein)		0.1069***					0.0907***	0.0900***
		(0.03)					(0.03)	(0.03)
Dietary Diversity (DD)			0.0130**				0.0092	0.0090
			(0.01)				(0.01)	(0.01)
Dietary Knowledge (DK)				0.0036*				0.0033*
				(0.00)			(0.00)	(0.00)
Food preference (FP)					−0.0066*			−0.0068*
					(0.00)			(0.00)
Dining Out (DO)						0.0045		0.0003
						(0.01)		(0.01)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values [a]	Y	Y	Y	Y	Y	Y	Y	Y
Observations	30971	30971	30971	30971	30971	30971	30971	30971
No. of individuals	14655	14655	14655	14655	14655	14655	14655	14655

Notes: Marginal effects are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. RE refers to random-effects estimator, and MK refers to Mundlak estimator.
Source: Author's estimation using the CHNS data (2004–2011).
*p < 0.10, **p < 0.05, ***p < 0.010.
[a]Mundlak mean values include mean values of other control variables except gender.

Table A7
Estimation of the impact of family income on BMI and overweight by gender when controlling for all channel variables.

Subsample	BMI				Overweight			
	Male		Female		Male		Female	
	RE	MK	RE	MK	RE	MK	RE	MK
LogM	0.024***	0.012**	0.007	0.007	0.0065*	0.0026	0.0014	0.0014
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Nutritional Intakes (NI):								
Log (Carbohydrate)	−0.182**	−0.089	−0.108	−0.080	−0.0460	−0.0183	−0.0393	−0.0308
	(0.08)	(0.06)	(0.08)	(0.06)	(0.03)	(0.03)	(0.04)	(0.04)
Log (Fat)	−0.003	−0.000	−0.020	−0.021	0.0100	0.0124	−0.0149	−0.0154
	(0.04)	(0.03)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Log (Protein)	0.206**	0.121	0.132	0.125	0.1170***	0.0875***	0.0889	0.0841*
	(0.10)	(0.08)	(0.11)	(0.10)	(0.02)	(0.03)	(0.06)	(0.05)
Dietary Diversity (DD)	0.036***	0.022***	0.031	0.027	0.0151***	0.0103**	0.0101	0.0089
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
Dietary Knowledge (DK)	0.029***	0.011	0.010	0.005	0.0104***	0.0028	0.0058***	0.0037*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Food preference (FP)	0.007	0.001	−0.021	−0.027	−0.0029	−0.0051	−0.0054	−0.0075
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Dining Out (DO)	0.029	0.020	−0.022	−0.017	0.0154*	0.0114	−0.0167**	−0.0139***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Other control variables	Y	Y	Y	Y	Y	Y	Y	Y
Mundlak mean values [a]		Y		Y		Y		Y
Observations	14764	14764	16207	16207	14764	14764	16207	16207
No. of individuals	7060	7060	7595	7595	7060	7060	7595	7595

Note: Coefficients for BMI are presented with standard errors in parentheses. Marginal effects for overweight are presented with standard errors in parentheses. Standard errors are cluster-corrected at province level. RE refers to random-effects estimator, and MK refers to Mundlak estimator.
Source: Author's estimation using the CHNS data (2004–2011).
*p < 0.10, **p < 0.05, ***p < 0.010.
[a] Mundlak mean values include mean values of other control variables except gender.

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