Does income growth improve diet diversity in China?

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Abstract

Recent studies on income and nutrition suggest that income growth plays either a small or even a negative role in influencing diet quality in China, especially for low income households. Such arguments cast doubt on the conventional reliance on income as a policy tool to improve public health through better diets. They, however, have been drawn mostly from analysis of income effect on nutrient intakes and diet adequacy. No research has been done on how income affects diet diversity in China, despite its unambiguous health benefits. This paper tests if income growth improves diet diversity, and, thus, can enhance public health in China, using data from the China Health and Nutrition Survey 2004-2009. For the first time, potential endogeneity of income, most likely due to omitted variables, is addressed in the estimation of income effect on diet diversity by instrumental variables. This study finds that, regardless of estimation methods, income effect is significant and positive, but diminishes along the income distribution and over time. When endogeneity of income is controlled in 2SLS estimation, estimated income effect is considerably larger than the corresponding OLS estimate. OLS regression shows that education has significant and positive effects on diet diversity, with larger effects at higher education levels. Nevertheless, education effects diminish in terms of both magnitude and statistical significance in the 2SLS estimation. The stark differences between OLS and 2SLS estimates suggest that it is important to account for endogeneity of income. The OLS estimation seemingly understates income effects and overstates education effects. It, therefore, might mislead resource allocation in designing food and health policies.

I. Introduction

Nutrition research has revealed a structural shift in food consumption patterns in developing countries over the last few decades. Consumers have shifted away from diets of varying nutritional qualities based on local grains, vegetables, and fruits toward diets higher in edible oil and animal-source foods yet less diversified in nutrients and lower in fiber. This so-called nutrition transition, or convergence to the 'Western' diet, is leading to significant increases in non-communicable diseases and substantial changes in disease patterns of the population. Obesity risks are shifting to the poor (Popkin 2004; Popkin & Gordon-Larsen 2004; Caballero 2005). Stroke, hypertension, and other diet-related chronic diseases are increasing in both relative and absolute terms as causes of mortality and morbidity (Popkin *et al.* 2001, p.3). Empirical evidence has also warned that increasing income does not necessarily improve diet balance (Du *et al.* 2004) and adequacy (Banerjee & Duflo 2011), especially for low-income people.

These warnings related to the detrimental health effects of changing diet as income rises seemingly contradicts conventional food and nutrition policies. Resources allocated to alleviate dietary problems, particularly through income-based programs or price subsidies, have often been justified by the conventional wisdom that calorie and nutrient deficiencies are largely a consequence of low income. If income growth in developing countries deteriorates diet quality and adversely affects the population's health, how should diet-related health issues be addressed? The question of practical interest becomes, How much (if at all) increasing income enhances or lowers diet quality, and consequently, public health? And is there any other policy instrument that can improve diet quality? However, diet quality is a multi-dimensional, encompassing adequacy, variety, moderation and overall balance of various nutrients. An answer to these policy questions, thus, might depend on the aspect of diet quality being investigated.

An ample body of research on nutrition, health, and labor market outcomes has been devoted to examining the relationship between income and diet adequacy. On the one hand, where hunger and nutrient deficiencies are the most daunting dietary problems, assessing the income impact on nutrient and/or food consumption quantity remains relevant and important. On the other hand, the nutrition transition that many developing economies have been facing is characterized not by a shortage of foods, but by a structural shift in patterns of food consumption. This requires that the income-diet relationship is examined from angles other than diet adequacy. One prominent candidate is diet diversity.

Economic studies on diversity of food consumption[1], however, have been confined mostly in explaining the demand for diversity by consumer theories. Little has been explored about what income effects on diet variety mean in (i) understanding diet issues associated with income growth and (ii) mitigating their adverse effects on health.

China presents a dynamic and academically attractive case of nutrition transition. Its rapid economic growth in the last three decades has brought significant improvements in income and living standard, as well as widening inequality across the country. Like many other emerging

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[1] In this paper, the terms *diet variety*, *diet diversity*, and *food consumption diversity* are used interchangeably.

economies, China has been experiencing the nutrition transition in the last two decades, and there is evidence that the transition is accelerating. Some studies have found evidence that rising income in China does not solve some key micronutrient deficiencies (Liu & Shankar 2007) but increases consumption of high-fat low-fiber foods (Du *et al.* 2004, p. 1512). However, little has been known about changes in diet diversity in this country. The sheer size of China's population, the pressing demand to maintain its economic competitiveness through higher labor quality, and the neck-breaking pace in which things have been happening there requires a better understanding of how much income determines changes in the structure and quality of the Chinese diet.

Inspired by this gap in the literature, this paper tests the hypothesis that income growth improves diet diversity, and, hence, can offset detrimental effects of the nutrition transition on health in China during the period from 2004 to 2009. This study also explores the role of another key policy instrument – education – in determining diet diversity. By investigating the effects of these two instruments, this policy-oriented research will hopefully shed lights on how government can influence diet diversity through income- and education-based programs. Using data from the China Health and Nutrition Survey, the study constructs a measure of diet diversity from the number of food groups consumed. It then addresses the potential issue of endogeneity of income by two-stage least square (2SLS) estimation method.

The contribution of this study is threefold. First, it provides new insights into the changes in diet quality as income rises in China. Proving positive and significant income effect on diet variety, this study argues that net income effect on diet quality, and, consequently, net effect on health, is not as negative as documented in the existing literature. This finding re-emphasizes the role of income in improving diet-related utility and labor health. The paper also takes the literature one step further by dissecting the analysis by region and shows that income effect is stronger in rural areas.

Second, this is the first study that addresses the potential issue of endogeneity in the link between income and diet variety by instrumental variables. To the best of the author's knowledge, potential endogeneity of income has been neglected by the existing empirical works on diet diversity, though some research has taken into account the endogeneity of total calorie intake (Drescher *et al.* 2009) and nutrition information (Variyam *et al.* 1998). This research argues that the existence of income endogeneity might be qualitatively debatable. The Durbin-Wu-Hausman test, however, detects its presence in the examined data. Estimates from OLS and 2SLS methods show stark differences and indicate that OLS method might underestimate income effects while overestimate education effect on diet diversity.

Third, this study has an advantage over the existing empirical studies in term of data quality. It uses individual food consumption data, instead of household food expenditure, and, thus, avoids aggregation errors of household level data in measuring individual consumption. The data employed are also the most up-to-date nutritional data available for China. The nutrition transition in China has been documented commencing as early as the early 1990s (Popkin *et al.* 2001). Yet the time frame of the empirical literature on changes in dietary consumption in China has not reached beyond the year 2001. Rapid economic and demographic changes in this country and evidence of inconstant income elasticities of nutrition consumption (Du *et al.* 2004)

discourage from making inference about the current situation from results of the 1990s. This study attempts to bridge this gap by situating our analysis in the most recent period 2004-2009.

The remainder of this paper is organized as follows. Section 2 provides a critical review of empirical research on income effects on dietary consumption behaviors, highlighting knowledge gaps where this study hopes to fill in. Section 3 describes the data set and points out the advantage of better data quality over existing empirical studies. Econometric models and rationales for variables used in this study are presented in Section 4. Section 5 analyses estimation results, and compares and contrasts them with existing evidence in the literature. Section 6 concludes with some policy implications and suggestions for further research.

II.   Literature review

The empirical studies on income as a determinant of dietary consumption can be broadly categorized based on their dependent variables and how they analyze consumption. One category, which is substantially more common, is devoted to explaining income effects on consumption quantity of calorie, nutrients, and foods. The other investigates the role of income on consumption patterns, including composition and relative share of different nutrients and foods.

2.1 Income effects on dietary consumption – calorie, nutrient, and food

A conventional belief is that low energy and nutrient intakes are largely a consequence of low income. However, the literature has not reached a conclusive agreement on the extent that income drives calorie and nutrient consumptions. An overarching analysis by Strauss and Thomas (1995) reviews 34 empirical papers and finds that estimated income elasticities of calorie intake range from 0.01 to 1.18. They explain some of this wide range by methodological differences. Estimated elasticities that are calculated indirectly from food demand equations tend to be higher (ranging from 0.51 to 1.18) whereas direct estimates from calorie demand equations tend to be considerably smaller (ranging from 0.56 to 0.01). An earlier study by Behrman and Deolalikar (1987) had also made the same remark about the two approaches to estimate nutrient elasticities with respect to household expenditure or income. The authors then argue that "the direct estimates probably lead to better, though still possible upwardly biased, estimates" (p. 496).

Methodological differences, however, do not fully account for variations in income elasticity estimates. Many studies have found a concave relationship between income and calorie consumption, such as Pitt (1983), Chernichovsky and Meesook (1984), Garcia and Pinstrup-Andersen (1987), Sahn (1988) and Ravallion (1990). Calorie elasticity with respect to income or expenditure is found to be positive at low calorie intake levels and then flatten out at about 2,400 calories per capita per day (Strauss & Thomas, 1995, p.1903). Intuitively, calorie intakes are likely to respond positively to income among the poor, but as income rises the elasticity will decline, possibly to zero, or even become negative at high enough income levels.

More recent studies indeed find a negative association between income and calorie consumption, i.e., as household income increases, people eat less. An example is Subramanian (2001), who

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finds consumption of cereals, the cheapest and highest source of calorie, declines as income increases in India. Banerjee and Duflo (2011) further argue that people do not always rationally increase their food consumption as they have more money or as the real price of these foods fall. The authors argue that even the money that people do spend on food is not spent to maximize the intake of calorie or micronutrients. This article stresses that the poor or near poor might derive utility from food and other non-food consumption differently from what standard economic theories predict, and that many poor people are not hungry enough to seize every opportunity to eat more.

The relationship between income and nutrient consumption is even more complicated. Various researchers, such as Strauss and Thomas (1990), Subramanian and Deaton (1996), and again, Banerjee and Duflo (2011), suggest that among poor urban households, when income rises, getting more calories was not a priority, getting tastier foods was. The higher valued foods, however, do not necessarily have higher nutrient content. Furthermore, income effects vary across nutrients. For example, Skoufias et al. (2009) estimate income elasticity for various macro and micro nutrients in rural Mexico and find mixed results. They obtain positive income elasticities for fat, vitamin A and C, calcium, and iron, which have the largest deficiency in their sample. Nonetheless, for the poorest households, "deficiency of total energy, protein, and zinc is not accompanied by positive income elasticity" (p.657).

As we navigate the broad literature on income effects on dietary consumption, two important points come to our attention. First, the widely varied estimates of income elasticities of calorie and nutrient intakes caution against any generalization about both the direction and the magnitude of income effects on household dietary consumption. The relationship might be either positive or negative and the extent of income effect varies considerably across nutrients and countries of interest. Second, examining dietary consumption at the nutrient level might not suffice to inform about changes in diet quality, amidst the structural shift in consumption patterns associated with income growth. Economic studies that aim to understand the role of income in driving diet quality through changes in nutrient consumption, thus, have an intrinsic shortcoming embedded in their dependent variables.

The majority of empirical studies on the causal link between income and dietary behaviours use either the quantity of foods and/or nutrients consumed, or its log, or food expenditures as a measure of the dietary consumption. Particularly, household per capita food expenditure has long been employed to estimate income elasticities by authors such as Pitt (1983), Behrman & Deolalikar (1987), and Sahn (1988). Another variable widely used in estimating responsiveness of food consumption to household income and prices is log of food consumption. See, for instance, Guo et al. (1999) and Du et al. (2004). At the nutrient level, log of calorie intake has been used as the dependent variables in works by Ravallion (1990), Strauss & Thomas (1990), Skoufias (2002), and Meng et al. (2007). Others have chosen to examine log of macronutrients, namely fat, protein, and carbohydrate, and essential micronutrient intakes, such as iron and vitamins. Examples of these studies include Liu & Shankar (2007), Mangyo (2008), and Skoufias et al. (2009).

Using log of consumption quantity as the dependent variable is easy to interpret the estimated coefficients. The coefficient of log of income then is simply the income elasticity of the food or

nutrient consumption. Similarly, elasticities of food expenditure with respect to income can be easily drawn from demand equation using food expenditure as the dependent variable. These conventional dietary variables remain important in studying how income or other policy variables such as education and subsidies can improve social welfare through household meals, especially in the context of subsistence economies where hunger and nutrient deficiencies are serious issues.

Nutrient intakes, however, reveal limited information about diet quality and associated health consequences. Higher level of calorie intake does not necessarily bring along higher health benefit if the pre-existing level of calorie consumption is already adequate. As argued in Skoufias *et al.* (2009), a significantly positive relationship between calorie and income does not necessarily imply a higher consumption of essential nutrients since a higher income may simply results in households buying more food with higher calorie density but low nutrient content, such as instant foods and fast foods. In fact, marked shifts toward diets with higher energy density have been documented in many developing countries. See, for example, Popkin *et al.* (2001) and Popkin (2004). A similar argument applies when income elasticity for calorie is close to zero. As household income falls, calorie consumption might be maintained through substitution between and within food groups while the consumption of important nutrients may decrease drastically as household consumes less meat, egg, vegetables and milk. Vitamin and micronutrient deficiency, therefore, can exist as a condition independent of calorie adequacy (Subramanian 2001). Moreover, a surplus of some nutrients such as fat and salt, through excessive consumption of highly processed foods, can be even more harmful to health than a deficit of such nutrients. Investigating consumption of calorie and individual nutrients, thus, provide only a partial understanding about structural changes in diet quality and diet-related issues accompanying the nutrition transition.

At the food level, how consumption responses to income changes depends on the food of interest. Income is found to significantly decrease starchy foods and meat consumption, yet increase milk consumption among Portuguese men (Moreira & Padrao 2004, p. 7). The same study also finds that income changes do not affect consumption of vegetables, fruits, and fish. A more recent paper by Ecker and Wain (2008) finds similar results in Malawi. The authors show that income responsiveness is high for starchy foods, but relatively low for vegetables and fruits. They observe the highest expenditure elasticities in animal-source foods and meal complements such as cooking oil, sugar, and beverages (p. 22).

Changes in food consumption quantity reveal partly how composition of the diet evolves and thus, partly fill the gap left by studies on nutrient intakes. Nevertheless, it is important to note that more of a particular food group guarantees neither positive nor negative impact on health. It depends on existing health and nutrition conditions of the individuals. It will be useful, hence, to investigate a less ambiguous indicator of diet quality, more of which is synonymous with beneficial impact on health.

2.2 Income effects on diet variety

Diet variety deserves attention for two reasons: well-grounded, unambiguous beneficial effect on health and direct positive effect on utility. Amid the structural shift in diet patterns in developing countries, diet diversity becomes even more relevant in indicating a healthy diet.

The variety of food consumption has been studied as one dimension of consumer demand for diversity from both macroeconomics perspectives (such as trade, industrial organization) and microeconomics perspectives (such as consumption behavior). Most relevant to this paper is microeconomic theories explaining a preference for variety to an individual's consumption behavior. As Weiss (2011) points out, we might distinguish two different approaches that explain why consumers purchase a variety of products: "representative consumer models" and "characteristics models" (p. 5). While "representative consumer models" derive a demand for variety at the level of individual consumer, "characteristics models" typically explain it at the market level. The traditional "representative consumer models" approach, which is more relevant to the present study, views food diversity as a specific feature of the utility function. A representative consumer maximizes his/her utility subject to a budget constraint. Differences in the preference for variety are reflected in the curvature of the indifference curves and are expressed in terms of the relative quantity of each product in the consumption basket (Weiss 2011, pp. 5-6).

It is beyond the scope of this study to review all those models in detail. But a notable model often used as a theoretical background for empirical studies on food diversity is the hierarchic demand systems suggested by Jackson (1984). Jackson introduces a hierarchy of purchase in which only a subset of all goods available is actually consumed. Higher income allows additional goods to enter the consumption bundle, forming a systematic relationship between income and consumption diversity. As argued by Weiss (2011), however, theories often fall short in fully explain consumer demand for variety due to various factors, often unobserved, that influence consumption decisions. This is where empirical studies come into the picture. A brief summary of relevant empirical works on income effect on diet diversity is presented in Table 1.

Table 1: Empirical studies that look at income effect on diet variety

Author	Country	Measure of diet diversity	Food grouping	Food measurement unit	Estimation method	Main findings
Drescher & Goddard (2011)	Canada	Berry index	176 food groups	food expenditure	OLS and quantile regression	Positive log-log relationship between income and diet variety. OLS estimates: a 1% increase in real household annual income leads to about 12.7% increase in the Berry index. Quantile regression shows significantly different effects of independent variables across quantiles. A 1% increase in income results in an increase of 8.3% to 24.6% in the Berry index. Education is not included in the regression model.
Drescher et al. (2009)	Germany	Berry index; Healthy Food Diversity (HFD) index	133 food groups	no. of food portions	OLS and 2SLS, IV for total calorie intake	Positive and significant linear income effect. An increase of 1000 Euro in household adult-equivalent monthly per capita income results in an increase of 0.030 and 0.038 unit in the HFD and Berry index, respectively. Positive education effect.
Drescher & Goddard (2008a)	Canada	Berry index; count of food items	176 food groups	food expenditure	OLS	Significant concave quadratic relationship between income and food diversity. At the sample mean, an increase of 1000 Canadian dollars in annual household income per capita increases diet diversity by 0.115 food groups in 2001. Food prices, education and household size are not included in estimation models.
Drescher & Goddard (2008b)	Canada	Canadian Healthy Food Diversity index	176 food groups	food expenditure	OLS	Positive semi-log relationship between income and the Canadian HFD index. Estimated coefficient of log of annual household income per capita ranges from 0.015-0.046, depending on models and food guides used. That is, when household income per capita doubles, the index value increases by 0.015-0.046 units. Positive and increasing education effect.
Theil & Weiss (2003)	Germany	Berry index; Entropy index	149 food groups, excluding fruit and vegetables	food expenditure	OLS	Significant linear positive income effect. A 1000 DM increase in household monthly income leads to an increase of 0.03 and 0.02 units in the Berry and Entropy index, respectively. Schooling of the household's principle wage earner has almost insignificant effect. Out of seven education levels, only the lowest and 3rd lowest education level had lower diversity as compared to the highest level.

Moon *et al.* (2002)	Bulgaria	Count of food items; Entropy index	102 food items	food weight	Negative binomial II for count measure, OLS for Entropy index	Consumer preference for food variety exhibited difference patterns depending on the length of time allowed for measuring consumption. Positive and significant linear income and education effects regardless of the length of time period allowed for consumption and measure of diversity. Coefficients of household income ranges from 0.019-0.041 for count measure. However, factorial income and education variables were treated as continuous.
Hoddinott & Yohannes (2002)	10 developing countries	Count of food items	varies across 10 datasets	food weight	OLS	Diet diversity is positively associated with change in household per capita consumption and household per capita caloric availability. The results are independent of the methods used to estimation methods nor of the methods used to collect the dietary data (24 hrs vs. 7-day recall periods), although the magnitude of the impact differs. Approx. 0.65-1.11% change in household per capita consumption given a 1% change in diet diversity.
Lee & Brown (1989)	USA	Berry index; Entropy index	19 food groups	food expenditure	OLS	Positive effect of total food expenditure and food stamp income on diversity. Household expenditure was modeled in log form. Marginal impact at the sample mean of 1 additional dollar of household fortnightly food expenditure is 0.0021 and 0.0003 for entropy and Berry, respectively.
Lee (1987)	USA	Count of food items	153 food groups	food weight	OLS, Negative binomial II, Poisson	Positive linear income effect on diet diversity, regardless of estimation method. One additional dollar of household weekly food expenditure results in an increase of 0.0071, 0.0053, and 0.0074 food groups consumed in the OLS, Poisson and negative binomial II estimation, respectively.
Theil & Finke (1983)	30 countries	Herfindahl index; Entropy index	various	food expenditure	Maximum likelihood estimation	Significant positive income effect. Elasticity of the Entropy index with respect to real per capita income ranges from 0.058 in the richest country (USA) to 0.441 in the poorest (India).

The empirical literature on food diversity has been consistent in proving positive income effects on diet variety. In a multi-country analysis, Hoddinott and Yohannes (2002) use data from 10 developing countries and test whether household diet diversity was associated with household per capita consumption, a proxy for household income, and household per capita calorie availability. Their results show that on average a 1% increase in diet diversity results in a 1% increase in per capita consumption. Another study by Moon *et al.* (2002) finds positive linear income effect on diet diversity in Bulgaria, but magnitude varies depending on the reference period that diversity is measured. The authors emphasize that the length of reference period allowed for consumption is an important element in measuring the demand for food variety. Studies in developed countries have also found similar results. Thiel and Weiss (2003), for example, suggest that variety of German household food consumption linearly increases with income. Demographic factors such as numbers of children, residential location, and employment status of the housekeeping person are also significant in explaining diet diversity in their sample. More recent works by Drescher and Goddard (2008, 2011) examine household diet diversity in Canada and show evidences of a concave relationship between income and diet variety[2].

These studies, however, were mainly motivated by a curiosity about consumer preferences and decisions. Though some acknowledged health benefits of food diversity, diet diversity was often analyzed as one dimension of consumer demand for diversity. Hardly any study has been conducted with an explicit ex-ante focus on policy implication from diet diversity's determinants in light of the nutrition transition and its associated public health issues. A rare exception is Drescher *et al.* (2009). Finding positive income and education effect, and significant roles of behavioral variables, Drescher and colleagues explicitly suggest considering knowledge, age, and willingness to pay for healthy food when promoting healthy eating.

Another shortcoming of the existing literature is their econometric estimation. Given diversity as a feature of utility and the traditional diminishing marginal return, it is simplistic to assume a linear correlation between income and diversity, as done in Moon *et al.* (2002), Thiel & Weiss (2003), and Drescher (2009). (In fact, Moon *et al.* use categorical income data yet treat it as a continuous variable in their regression analysis.) Drescher and Goddard (2011), though allowing for non-linearity, fail to take into account education effect. Neither did the aforementioned papers address potential inverse causality in the link between income and diet diversity.

2.3 Income effects on dietary consumption and diet quality in China

Empirical research on the income-diet relationship in China has been consistent with the broader literature in terms of focusing on level of food and nutrient consumption. This body of research has also examined the structural shift of food consumption patterns, such as changes in consumption of animal-origin foods and grains. Among the most prominent studies on the income-diet relationship in China are Guo *et al.* (2000) and Du *et al.* (2004). Estimating income elasticities for a range of foods in China, Guo *et al.* (2000) conclude that income elasticities for more luxurious foods increased significantly from 1989 to 1993, while less superior foods became more inferior over this period. Similarly, Du *et al.* (2004) argue that important changes

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[2] Drescher and Goddard (2008a) suggest a concave quadratic relationship, while their more recent work in 2011 supports a semi-log relationship between income and diet diversity.

in income effects took place between 1989 and 1997, with the changes varying considerably by income groups. The authors warn that "these shifts in income effects indicate that increased income might have affected diets and body composition in a detrimental manner to health, with those in low-income groups having the largest increase in harmful effects due to highest income elasticities" (p. 1505).

At the nutrient level, Liu and Shankar (2007) model the determinants of the intakes of vitamin A and D and test whether rising income will likely help overcome these two micro nutrition deficiencies. Their results show a statistically significant but relatively small positive income effect on both nutrient intakes. The local availability of milk is seen to have a strong positive effect on intakes of both micronutrients. The paper then suggests that rather than relying on increasing income, food policies like school milk programs might be more effective in stamping out these vitamin deficiencies.

These results, together with other varying empirical results on the relationship between income and nutrition intake, question the conventional reliance on rising income to improve diet-related welfare in China. If rising income not only fails to improve diet quality, but might also deteriorate it, income growth is likely to reverse or at least dampen the achievement in public health thanks to hunger eradication. However, as discussed in earlier sub-section, the question of how much (if any) rising income improves diet quality in China deserves to be examined with a better and less ambiguous indicator of diet quality.

Moreover, to the best of the author's knowledge, there is still no empirical literature investigating the role of socioeconomic factors as a determinant of diet diversity in China. Evidences of a positive association between income and diet diversity in other countries encourage this paper to test if a relationship between income and diet variety exists in China, and if it does, what form it takes. I will also take the literature one step further by dissecting the analysis by geographic regions. This exercise will help determine if marginal effects of socioeconomic factors varies across population subgroups.

III.   Data and variables

3.1 Data

This study employs data at individual, household and community levels from the China Health and Nutrition Surveys (CHNS). The survey is an on-going longitudinal collaborative work between the Center of Population at the University of North Carolina at Chapel Hill and the Institute of Nutrition and Food Safety, Chinese Center for Disease Control and Prevention. The CHNS is one of the few datasets from developing countries that have information on individual food consumption and nutrient intakes over time, making it particularly suitable for examining the nutrition transition and household dietary behaviors.

The CHNS uses a multi-stage, randomized cluster design to survey approximately 3,800 households in nine provinces in China. The provinces are Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning, and Shandong. See Appendix 1 for a map of the surveyed provinces. The survey's sample, nevertheless, has no sampling weights and is not

representative at either province or national level. To control for multistage sampling and an array of multilevel modeling issues, this paper utilizes various levels of control, as discussed in more details in Section 3.2.

The sample is disaggregated into five administrative levels: (i) province, (ii) urban and rural, (iii) city and county, (iv) urban/suburban and town/village, and (v) household. Counties and cities in the provinces are stratified by income (low, middle, and high) and a weighted sampling was used to randomly select four counties and two cities in each province. The provincial capital and a lower income city were selected when feasible. Villages and townships within the counties and urban and suburban neighborhoods within the cities were selected randomly. In each community, 20 households were randomly selected and all household members were surveyed. Since 2000, the survey framework has contained 216 primary sampling units, consisting of 36 urban neighborhoods, 36 suburban neighborhoods, 36 towns, and 108 villages.

The dataset used in this paper is taken from three waves of the CHNS: 2004, 2006, and 2009. With a strong focus on the labor force, this paper limits the sample to 11,146 adults (18-60 years old) from 4,506 households, among which 3,891 individuals were interviewed in all three waves. After accounting for missing data, the actual regression sample size for the 3 years is 5,182, 4,971, and 5,010 observations, respectively. Geographical distribution of the sample is displayed in Figures 1 and 2.

Figure 1: Rural-urban distribution of dataset
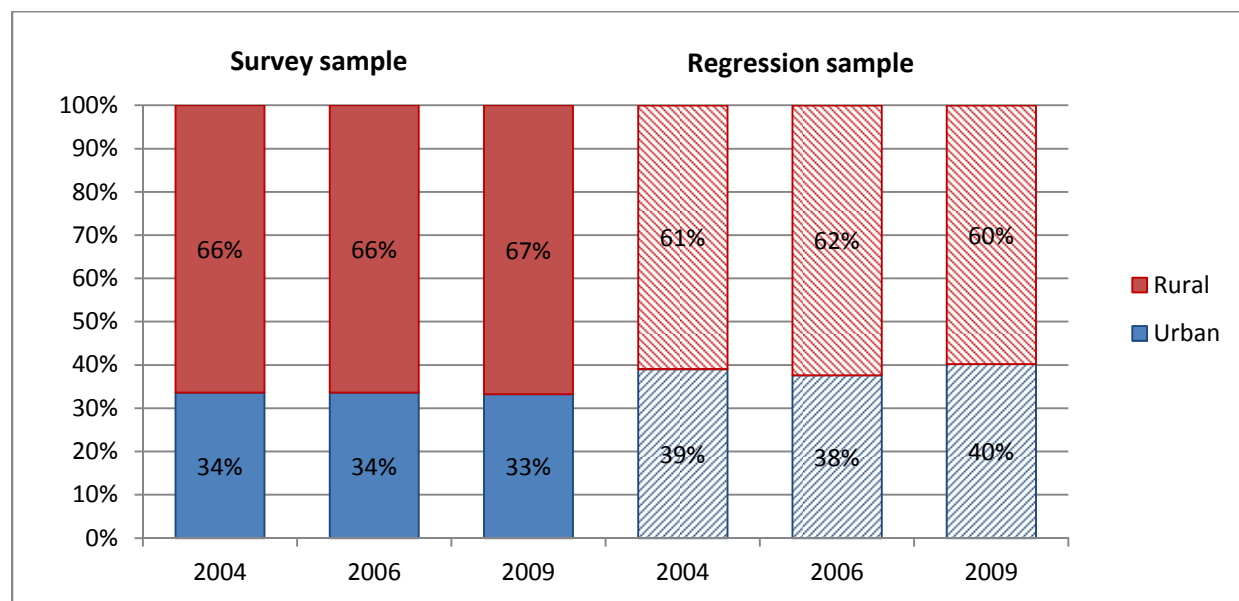
Figure 2: Geographical distribution of dataset
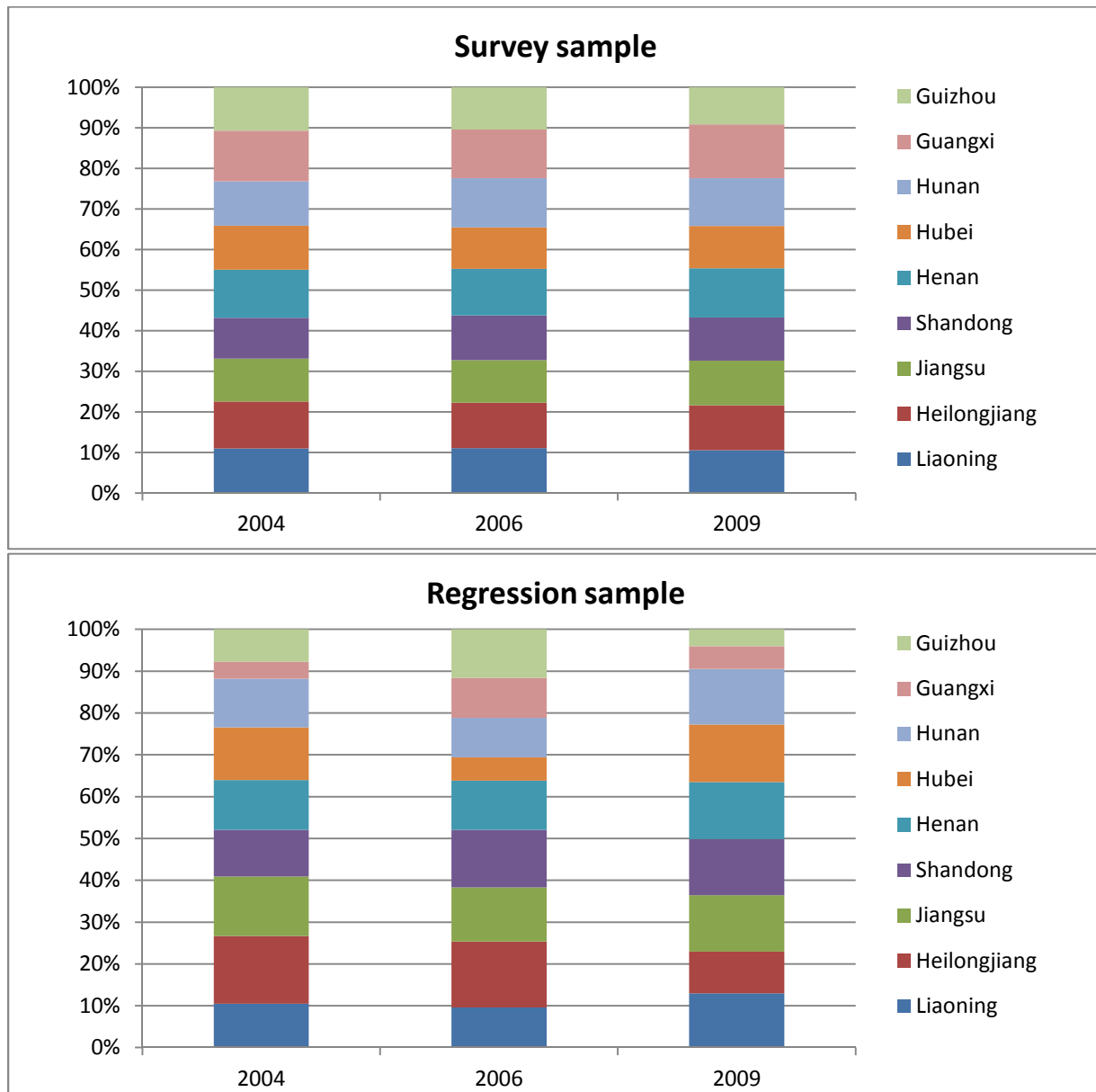
The detailed records of individual food consumption from the CHNS provide this paper an advantage over studies using household level data. Household food expenditure or food consumption data neglect the intra-household distribution of food and thus, impose aggregation errors in measuring individual consumption (Ecker & Wain 2008, p. 14). Besides, nutrient requirements and recommendations are defined for individuals of particular gender and age. Nutritional implication from household level data, thus, must be applied with caution to any specific demographic population groups by age or gender, which in many cases is of special interest.

3.2 Variables

3.2.1   Dependent variables

As mentioned in earlier sections, this paper investigates the relationship between income and diet quality in China from the angle of diet diversity. Two major reasons justify the usage of diet diversity as an indicator of diet quality. First, the essential role of diet variety in maintaining good health is well-grounded and unambiguous in both the nutrition literature (Ruel 2002) and governmental nutrition policies. Improving the variety of food consumption across and within food groups is the first recommendation in most official dietary guidelines, including the Dietary Guidelines for Australian Adults (NHMRC 2003), Dietary Guidelines for Americans (USDA & USDHHS 2010), Dietary Guidelines for Chinese Residents 2007 and the Chinese Food Guide Pagoda 2007 (Ge 2011). Measures of diet variety have also been used as a component in various diet quality scores, such as the DQI Revised by Haines *et al.* (1999), INFH-UNC-CH DQI by Stookey *et al.* (2000), and DQI - International by Kim *et al.* (2003). Second, nutrition studies in developing countries have validated a positive relationship between dietary variety and nutrient adequacy[3]. Thus, diet variety is not only an informative indicator of diet quality, but could also be "a useful indicator of household food security" (Ruel 2002, p. iii; Ruel 2003).

Having justified the usage of diet variety as a dependent variable based on its health benefits, this paper closely follows the nutrition literature in measuring diet variety. Diet diversity is often measured using a simple count of foods or food groups over a reference period, but several foods grouping and classification systems have been used (Ruel 2002). To generate a measure of diet variety applicable to the Chinese diet, this study follows the Diet Quality Index – International developed by Kim *et al.* (2003) and constructs our variety variable as follows. A well-diversified diet should consist of foods from all 5 broad food groups: grain, meat, vegetable, fruits, and diary. Although individual food items can be categorized according to different degrees of aggregation, these 5 broad food groups capture the main sources of important nutrients required for a healthy body.

The dietary section of the CHNS records individual's food intake on a 24-hour-recall basis for three consecutive days for each survey year. Food items are assigned into one of the five selected broad food groups based on the classification in the Chinese Food Composition Table (Yang *et al.* 2004, 2009). Diet variety then is measured as the average daily number of food groups consumed by an individual. Following Stookey *et al.* (2000), a food group is counted if its daily consumption quantity is larger than 25 grams. This amount is deemed to be nutritionally meaningful. Our diet variety variable is, thus, on a range from 1 to 5.

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[3] Ruel (2003) provides a careful review of studies that validate diet diversity against nutrient adequacy, child nutritional status and growth.

Table 2: Distribution of dependent variable

Count of food groups consumed	2004	2006	2009
Frequency			
1	2	2	1
2	502	316	174
3	1,753	1,573	1,253
4	2,298	2,241	2,352
5	627	838	1,230
Total	**5,182**	**4,971**	**5,010**
Mean	3.52	3.68	3.85
Std. Dev.	0.81	0.81	0.79

As can be seen in Table 3, diet diversity is relatively concentrated around its mean and increases over time. Though the concentration of the variable might raise some concerns, the regression results presented in later sections suggest that the data have enough variation to generate significant estimated relationships.

It should be noted that alternative measures have been used in the economics literature. Popular alternatives include the Berry index (or the Simpson index) (Berry 1971; Lee & Brown 1989; Drescher & Goddard 2008, 2011; Theil & Weiss 2003), the Entropy index (Lee & Brown 1989; Moon *et al.* 2002; Theil & Weiss 2003), and the Healthy Food Diversity Index (Drescher *et al.* 2007, 2009). A less popular measure is the Hirschman-Herfindahl index, used by Theil and Finke (1983). These measures take into account the relative share of each food group consumed within the total food consumption, while a count measure does not.

Despite this advantage, they are ruled out for two reasons. First, their values are difficult to interpret in absolute terms. This imposes a challenge for policy making when we are concerned about policy implication from estimated effects of policy instruments like income and education. Second, the more popular Berry index and Entropy index only measure the degree of consumption diversity but does not reflect health benefits of diet diversity. These two indexes are higher when a larger number of foods are eaten in equal shares. From a nutritional perspective, nonetheless, foods should be consumed according to recommended quantities and relative shares, not in equal share. In this sense, these indexes are not better than a count measure in terms of capturing health aspects of a diversified diet.

Probably the only diversity measure that attempts to incorporate the health value of a food basket is the Healthy Food Diversity index proposed by Drescher *et al.* (2007). Building on the Berry index, the authors introduced a health factor for each food group based on the food pyramid of the German Nutrition Society. This pyramid, unfortunately, is hardly applicable to the Chinese diet. It illustrates dietary recommendations for the German population, which has very different cuisines, food availability, and biophysical conditions from its Chinese counterpart. Moreover, the health factors are calculated by multiplying the quantitative and qualitative dimensions of the recommended foods. These "graphically depicted qualitative dimensions" in the pyramid are quantified by assigning a percentage value to each food group (Drescher *et al.* 2009, p. 686). In a later study, the authors note that such "explicit valuation of foods is an own interpretation of the

German Food guidelines" (Drescher *et al.* 2009, p. 686). The health factors used to calculate the Healthy Food Diversity index, thus, may be ad-hoc.

3.2.2 Independent variables

A key explanatory variable in our study is real annual household income per capita, inflated to 2009 price. Household income per capita has been adjusted for the adult equivalence scale to account for differences in consumption of household resources by members of different ages. This paper employs the modified OECD adult equivalent scale. The first adult in a household is counted as 1, each of the other adults as 0.7, and each of the children younger than 18 years old as 0.5. Summary statistics of household income in Table 4 show considerable inequality across provinces. Mean income of the poorest one is about 50%, 46%, and 55% of that of the richest in 2004, 2006, and 2009, respectively. Although income rise is rapid by international standard in all provinces, the specific growth rate varies. The highest annual accumulated rate between 2004 and 2009 is observed in Hubei (16.4%) and lowest in Jiangsu (4.8%).

Other explanatory variables likely to affect food consumption include community- and household-specific characteristics as well as individual demographic information. At the community level, province dummy and rural dummy variables are modeled in order to control for differences in dietary tradition, general lifestyle, and food availability across regions. Potential price effects are taken into account by controlling for food prices at community level. The model includes prices of rice, pork, fish, cabbage, tofu, apple, and soy oil, as representatives of grain, meat, vegetables, bean products, fruits, and edible oils, respectively. All price variables are in log form and measured in Yuan.

A household-specific characteristic that might influence food consumption is household size. Again, this variable is adjusted to the modified OECD adult equivalent scale. Adjusted household size is then the adjusted number of household members.

Education is conventionally modeled in demand equations as an indicator of knowledge and, thus, is expected to affect consumer's behaviors. In the context of this study, education of an individual is expected to determine his/her food consumption decisions. In order to allow for a flexible relationship between education and diet variety, the highest level of education attainment is categorized into 6 groups: no formal education, primary school, secondary school, high school, vocational training, and university and higher. This ordered factorial variable will be able to capture impact of having a higher level of education on diet variety, without imposing a rigid and possibly controversial relationship between years of schooling and the dependent variable.

Other relevant individual demographic variables[4] include age, gender, and daily average food consumption, measured in kilograms. The daily average quantity of food consumed will help control for the changes in number of food items consumed as quantity of food intake changes. Occupation, though, might reflect variation in lifestyle and dietary habits, is highly correlated with education and at least partly with household income, and thus, is not included in this model. Summary statistics for all explanatory variables are shown in Table 4.

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[4] Since more than 88% of our sample belongs to the Han ethnic group, leading to little contrast in the data, we do not include ethnicity in our model.

Table 3: Summary statistics of independent variables

Variables	2004		2006		2009	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	42.00	10.77	42.87	10.68	43.31	11.02
Gender (% of female)	52.1%		52.3%		52.2%	
Household size	3.47	1.25	3.58	1.38	3.48	1.35
Education						
Years of schooling	8.68	3.90	8.64	4.23	9.02	4.05
No education	11.2%		15.4%		12.6%	
Primary school	21.6%		17.5%		15.5%	
Secondary school	36.7%		35.8%		39.3%	
High school	17.2%		16.6%		16.5%	
Vocational training	8.2%		7.9%		8.8%	
University and higher	5.1%		6.9%		7.3%	
Real annual household adult-equivalent per capita income(2009 Yuan)						
Overall	10,033	9,547	11,436	16,396	16,215	21,658
Liaoning	10,837	10,287	12,712	11,864	16,245	17,633
Heilongjiang	10,261	9,274	12,029	14,338	16,750	19,680
Jiangsu	15,880	12,037	14,244	14,681	19,610	17,695
Shandong	8,617	7,852	13,315	27,232	17,106	23,641
Henan	6,720	6,136	9,126	11,458	12,568	15,555
Hubei	7,854	8,017	11,386	25,796	14,983	22,393
Hunan	10,252	9,534	11,758	14,862	17,596	32,049
Guangxi	8,546	7,169	7,184	5,564	13,155	17,567
Guizhou	8,521	8,706	9,785	11,047	16,459	19,249
Prices (Yuan per kg / liter)						
Rice	1.27	0.21	1.38	0.23	1.66	0.68
Pork	7.12	1.27	5.93	1.15	9.18	1.43
Fish	4.77	4.13	4.10	0.96	5.08	1.40
Cabbage	0.67	2.45	0.83	1.42	1.01	0.83
Tofu	2.53	1.52	2.28	1.04	3.33	1.49
Apple	1.37	0.73	1.88	0.76	2.44	0.90
Soy oil	4.09	1.41	3.81	1.30	5.04	1.90

IV.   OLS models and estimated results

4.1 OLS models

This paper assumes that the functional forms of the relationship between diet variety and explanatory variables do not change over the examined period. For each surveyed year, the OLS regression equation is specified as follows[5]:

$$Variety_{ijk} = \beta_1 + \beta_2.food_{ijk} + \beta_3.Y_{jk} + \beta_4.I_{ijk} + \beta_5.H_{jk} + \beta_6.C_k + \varepsilon_{ijk} \quad (1)$$

where *i, j, k* indicate individual, household, and community, respectively. $Variety_{ijk}$ is the variety of the diet consumed by individual *i* in household *j* at community *k*. $food_{ijk}$ is the 3-day average quantity of foods consumed by individual *i*, measured in kilograms. Y_{jk} is a vector of household income variables of household *j* in community *k*. I_{ijk} is a vector of individual demographic variables. H_{jk} and C_k are vectors of household-specific and community-specific characteristics, respectively. ε_{ijk} is the individual-specific error term.

Since the literature does not provide a universal guide about the functional form of the relationship between diet variety and income, this research experiments with 4 model specifications. The simplest one uses real household income per capita as the only income regressor, assuming constant marginal income effect. This diagnostic model is expected to roughly inform about the direction of the relationship of interest.

Assuming a linear causal link between income and diet variety, however, is likely to be simplistic. Drescher and Goddard (2008a) find a concave quadratic relationship significant at 1% level, while their more recent work in 2011 supports a log-log relationship between income and diet diversity. Besides, the existing literature on income effect on calorie intake has also found an increasing concave relationship between income or expenditure and calorie intake through both parametric and semi-parametric approaches. Several studies have also included a quadratic term in income or expenditure and found a concave relationship. For example, see Garcia and Pinstrup-Andersen (1987), Sahn (1988), and Ravallion (1990). Nevertheless, a quadratic form may not always be sufficient to capture to nonlinearity. For instance, in descriptive studies, Poleman (1981) and Lipton (1983), cited in Strauss & Thomas (1995), argue that the calorie-income curve may be v-shaped. A related, but stronger hypothesis, also postulated by them, is that the budget share of foods may actually increase with income for very poor households. More recent evidence shows that income elasticity of calorie intake is positive and very high among

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[5] By construction, the dependent variable in this paper is count data, ranging from 0 to 5. Using OLS method with a censored non-negative dependent variable may be inappropriate since OLS method does not impose any restriction on the predicted value of the left hand-side variable. In order to assess how the count data nature of diet variety measure might complicate the estimation approach, a Poisson regression model is tested, with robust adjustment for unknown form of variance:

$$Pr(Variety = y) = \frac{e^{-\mu} * \mu^y}{y!} , \quad y = 0, 1, 2, 3, 4, 5$$

where $\mu = \exp(x'\beta)$, x and β are vectors of explanatory variables and parameters as explained in equation (1).

However, estimates from OLS and Poisson regression are closely similar. The author believes, thus, it makes little difference to account for count data specifically and the technical challenges do not outweigh the benefit.

poor households, but the curve flats out when calorie consumption reaches about 2400 kcal/day (Strauss & Thomas, 1995). These empirical findings hint that the present relationship between diet diversity and income might display similar nonlinearity.

These possibilities are tested by models 2 and 3. The second and third specifications model quadratic and semi-log relationship between income and diet variety, respectively. Of course, quadratic and semi-log are only basic ways of dealing with nonlinearity. The last specification uses income quintiles to avoid imposing a rigid function of nonlinearity yet still allow for variation in income effects across income groups.

Statistical software STATA, version 11.0, is used to clean the datasets and implement all analyses. The empirical analysis begins by formally testing the presence of heteroskedasticity by the Breusch-Pagan test across all years and model specifications. The test statistics strongly reject the presence of constant variance of the error term and hence, justify the employment of the *robust* option in estimating coefficient variance.

4.2 OLS estimates: Income effects

OLS estimated coefficients of real household income per capita are presented in Table 1 for all four model specifications. For brevity, the full set of OLS estimated results is provided in Appendix 2. Standard errors in this appendix and elsewhere in this paper are all robust to heteroskedasticity.

Table 4: OLS estimated coefficients of real household income per capita

Model	Variable	2004	2006	2009
1	Income	0.078***	0.013*	0.009**
2	Income	0.189***	0.083***	0.031***
	Income squared	-0.022***	-0.005***	-0.001***
3	Log of income	0.090***	0.067***	0.039***
4	Quintile 2	0.092***	0.103***	0.036
	Quintile 3	0.157***	0.191***	0.062*
	Quintile 4	0.237***	0.253***	0.045
	Quintile 5	0.307***	0.274***	0.151***
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				

The "diagnostic" model 1 suggests that household per capita income has a positive, yet decreasing impact on diet variety over the examined period. The estimated coefficients of income decline in terms of both magnitude and statistical significance over time.

Model 2 reveals a concave quadratic relationship significant at 1% level between diet variety and income. This result dictates that as income increases, diet variety will be improved at a diminishing rate until it reaches a maximal point, from which onwards, diet variety will fall. However, holding all other explanatory variables in the model constant, the maximal point of diet variety is achieved at an annual household income per capita of 42.6, 91.2, and 138.6

thousands Yuan in 2004, 2006, and 2009, respectively. These optimal levels of income are well above the mean income of the richest quintile in their respective years. Only 3.05, 2.64, and 2.30% of the regression sample have income higher than these optional values in the three respective years. In other words, income of the majority of examined sample is still low enough to guarantee an improvement in diet variety as it rises. Although the exact magnitude of income's marginal effect depends on the level of household income, this finding supports our intuitive expectation that higher earnings allows for a broader consumption basket, and thus, a more diversified diet.

The exceptionally high values of optimal income levels, relative to most of the income distribution, also raise a caution. The concave quadratic relationship, though statistically significant, might be due to some outliers that have extremely high income yet relatively lower diet variety than those with lower income and similar non-income characteristics. These few observations give grounds for suspecting that the true relationship between income and diet variety might be positive and concave, but not necessarily quadratic. This suspicion is further enforced by previous empirical works. As discussed in the previous section, the literature has suggested that a quadratic form may not always be sufficient to capture nonlinearity in income effects.

Turning to the hypothesis of a semi-log relationship between income and diet diversity, this study finds that income effect flattens in 2009. The coefficient of log of income is simply the marginal change in diet variety as income doubles. In 2004, when annual household income per head is doubled, diet variety increases by approximately 0.09 food groups. The figure drops to 0.04 food groups in 2009. This pattern of decreasing income effect seems to follow the same line of findings in models 1 and 2.

Comparison between the quadratic and semi-log specifications is made by calculating marginal income effect at different points along the income distribution. Figure 3 below presents the estimated marginal change in diet variety as real household income per capita rises by 1000 Yuans (approximately USD146). The marginal effect is computed at six different points: the sample mean and the mean of each income quintile. On average, the estimated marginal effect at the sample mean is higher in the quadratic model. The semi-log model yields a steeper slope at the lowest income quintile, yet flats out faster as income increases.

Figure 3: Estimated marginal impact of 1000 additional Yuan at mean income
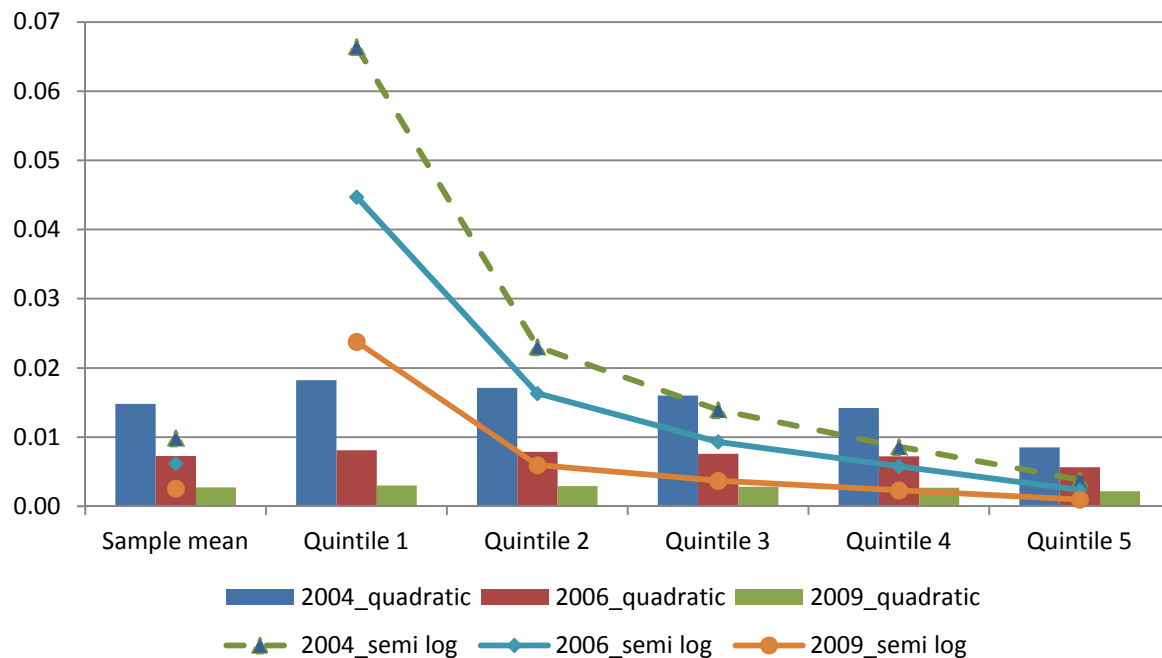
Differences in categorizing food items and measuring diversity make it hard to compare magnitude of the present estimated coefficients with existing evidences. Nevertheless, all three models above produce consistent estimates with those of earlier studies in terms of sign and statistical significance, namely a positive linear income effect found by Moon *et al.* (2002), Theil and Weiss (2003), and Drescher *et al.* (2009), a concave quadratic income-diversity relationship in Drescher and Goddard (2008), and a log-log relationship in Drescher and Goddard (2011). See Table 6 below for a rough comparison of this research and existing empirical results. A more detailed summary of these studies is displayed in Table 1.

More importantly, the tested non-linear relationships both suggest that diet variety of low-income people is more responsive to income changes than that of the rich. Income programs, thus, provide a straightforward channel to promote healthy eating among this vulnerable group.

Table 5: Comparison of OLS estimated income effect with existing empirical results

Model	Relationship	Estimated marginal impact of 1000 additional Yuans/Dollars/Euros	
		This study	**Existing studies**
1	Linear	0.0014- 0.0085 food groups	• 0.019-0.041 food groups (Moon *et al.* 2002) – income measured as a factorial variable, food group ranges f • 0.02-0.03 units of Berry and Entropy index, respectively (Theil & Weiss 2003) – income measured in Deutsche Mark • 0.030-0.038 units of HFD index (Drescher *et al.* 2009) – income measured in Euro
2	Quadratic	0.0039-0.0104 food groups	• 0.080-0.138 food groups – income measured in Canadian dollar (Drescher & Goddard 2008a)

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3	Semi-log	0.0015-0.0055 food groups	• 0.0013-0.0014 units of Canadian HFD index (Drescher & Goddard 2008b) – income measured in Canadian dollar

Releasing the rigid functional forms above, model 4 estimates impact of being in the second, third, fourth, and fifth quintile relative to being in the poorest one. Its results, shown in the last panel of Table 5, corroborate that there is a positive link between income and diet variety, yet income effects vary across income groups. Compared to the poorest 20% of the sample, the diet of the richer quintiles contains approximately 0.1 to 0.3 more food groups in 2004 and 2006. The relative differences among the quintiles, however, seem to narrow over time. In 2009, only the richest quintile has a better diet in terms of variety than the base quintile, tested at 1% level. Again, this proves a diminishing role of income in influencing diet diversity over time.

Going beyond analysis within each survey year, we are particularly interested in how the income effect evolves across the three cross sections. As shown in Table 5 and Figure 3, despite their different functional forms, all models show that estimated income coefficients fall over the examined period.

Two important points arise as we focus on the decrease in marginal income effects over time. First, these changes can be partly explained by the underlying income growth. *Ceteris paribus*, a higher income level in a later year indicates a shift to the right along the relationship function, *i.e.* to the flatter portion of the curve. Thus, even if the relationship remains unchanged over time, income growth leads to lower income marginal effect on diet variety. The relative changes in income effects are consistent with the income growth rates of the two periods 2004-2006 and 2006-2009. Income marginal impact drops relatively less during 2004-2006 than during 2006-2009. This is matched by a lower growth rate of mean household income per capita during the earlier period (8.6% per annum) as compared to 11.9% in the later. Second, the slope of the estimated relationship declines, causing lower marginal income effects over the examined period. A possible explanation for this lies in the nature of the data. Assume the true relationship is concave and remains constant over time. The observed sample, however, move towards the right tail of the income distribution. In other words, the sample contains more observations on the flatter section of the true relationship. Linear estimation, which is based on the observed data, then detects flatter slope and yields smaller estimated coefficients.

To compare the above specifications, model selection criteria AIC and BIC are employed. As can be seen in Appendix 2, the semi-log model (model 3) yields the lowest AIC and BIC values, and thus, should be preferred among the tested specifications. Henceforth, we will interpret estimated coefficients of the remaining explanatory variables from this model

4.3 OLS estimates: Education effects

Table 6: OLS estimated coefficients of education

Education level	2004	2006	2009
Primary	0.122***	0.026	0.113***
Secondary	0.258***	0.192***	0.165***
High school	0.398***	0.300***	0.255***
Vocational training	0.587***	0.492***	0.387***
University & above	0.572***	0.398***	0.405***
* p < 0.10, ** p < 0.05, *** p < 0.01			

Table 8 displays estimates of coefficients of five education levels from model 3, as compared to the base group (no education). Except individuals with only primary school education in 2006, formally educated consumers consistently have higher diet diversity than the base group, who had no formal schooling, across the three examined years. Generally, the higher the education attainment, the larger the difference in diet diversity as compared to the base group. Although the estimated coefficient for vocational training is slightly higher than that for university education in 2004 and 2006, they are not significantly different from each other even at 10% level (F statistics=0.10, p-value=0.76). This monotonic pattern of positive and increasing impacts of education on diet variety is not surprising. Better educated people are likely to be more knowledgeable and/or more concerned about health and nutritional balance. So on average, they make better informed food consumption decisions. The positive role of education and knowledge in influencing food choices has also been detected earlier in OLS estimation by Variyam *et al.* (1998), Moon *et al.* (2002), and Drescher *et al.* (2009), among others.

Interestingly, the coefficients of education attainments appear to fall over time. Keep in mind that these are the relative differences in diet variety between individuals with some education and the base group. These narrowing gaps between formally educated and uneducated consumers suggests that education might no longer as effective in improving diet diversity in 2006 and 2009 as it used to be in 2004. Probably more available information or changes in life style make diet of people with formal education not much more diversified than that of the base group as it used to be. Still, vocational training and tertiary education remain important in supporting healthy food consumption. A university graduate or vocational training graduate on average consumes about 0.4 more food groups per day than an individual without any education. That difference is about half of the standard deviation of diet diversity in each surveyed year.

4.4 OLS estimates: Effects of community factors

Given the vast geographical coverage of the sample, we expect local fixed effects to play an important role in shaping how diversified the diet is. Liaoning is used as the base province. As shown in Table 8 below, individuals from all provinces, except Jiangsu, consistently have lower diet diversity than their counterparts in Liaoning, tested at 1% level.

Table 7: OLS estimated coefficients of community factors

Community variables	2004	2006	2009
Province			
Heilongjiang	-0.481***	-0.251***	-0.457***
Jiangsu	-0.054	-0.082*	-0.507***
Shandong	-0.159***	-0.355***	-0.295***
Henan	-0.399***	-0.568***	-0.672***
Hubei	-0.379***	-0.604***	-0.727***
Hunan	-0.289***	-0.254***	-0.633***
Guangxi	-0.577***	-0.667***	-0.569***
Guizhou	-0.253***	-0.233***	-0.558***
Rural	-0.356***	-0.195***	-0.251***

$* \ p < 0.10, ** \ p < 0.05, *** \ p < 0.01$

Judging from the magnitude of the estimates of the provincial dummies, the relative differences among the estimates appear to follow neither the income variation across the provinces nor their geographical neighborhood. For example, Heilongjiang had significantly lower diet diversity than the omitted province, which had similar a mean income level in all 3 years. Similarly, Hubei's mean annual income in 2006 is 11,386 Yuan per capita, very similar to its neighbour Hunan (11,758 Yuan); yet the coefficient for Hubei is more similar to that for Guangxi, the poorest province of the year (7,186 Yuan per capita). The two neighboring coastal provinces Shandong and Jiangsu do not seem similar, either.

This observation suggests that the provincial dummies are likely to have captured impacts of non-income factors among the surveyed provinces. Those factors could be anything, but mostly unobserved, such as: culture and lifestyle, taste, food availability, cuisine, weather, etc.

Individuals living in rural areas have a less diversified diet on average than their urban counterparts. This could be attributed to a narrower range of foods available in rural areas. Food choice of rural residents might be constrained by the foods produced locally and/or shortage of non-traditional food such as milk and dairy products, which makes their diet less diversified.

V.   2SLS models and estimated results

5.1 2SLS models

An important issue which needs to be addressed, yet has been neglected by the literature, in modeling the relationship between diet variety and income is potential endogeneity. The causal link between income and diet diversity might be mutual. Diet variety, by promoting good health, could positively affect labor income through higher labor supply and/or higher productivity. On the other hand, higher income allows for a larger consumption basket and thus, might have a positive impact on diet variety. In this case, the OLS estimated income effect will be biased upward and the bias may be higher for low income earners.

Similar concerns about endogeneity of income have played a prominent role in the literature about income effect on nutrient intakes. Current nutrient intakes might raise labor supply and/or productivity, especially for jobs that require heavy physical effort. In a comprehensive review of this literature, Strauss and Thomas (1995) state that '… as well as endogeneity of income or expenditure, and the validity of instruments are all very important concerns' (p.1901). The same research also discusses the reverse relationship between nutrients and, more generally health, on income. The authors then stress that 'correlation between any component of income (such as wages or labor supply) and measure of health that depend on current behavior could reflect causality in either direction' (p. 1911). Empirical studies on the responsiveness of nutrient intakes to income have also paid special attention to controlling for inverse causality. Example includes Berhman and Deolalikar (1987), Bouis and Haddad (1992), and Skoufias *et al.* (2009).

If we believe in such inverse causality, the same logic could be applied to the correlation between income and diet diversity. In the context of this study, however, the presence of simultaneity is debatable. Diet variety, through nutrition effect on labor supply and productivity, may take a considerable time before it can influence income, while current income is very likely to directly impact current diet. Besides, if a household member does not contribute to the household's income through his/her labor supply, her dietary changes will have no effect on household income per capita. So if past and current diet varieties are not correlated, simultaneity is not present in equation (1).

Over and above concerns with simultaneity, endogeneity in this study is more likely to arise from omitted variables. Many unobserved factors could influence food choices and diet variety, such as taste, physical activity level, health condition, and consumer's perception about the social image that their foods project. For example, rich people might prefer to consume more expensive foods to prove their social status. It is also possible that taste for work and lifestyle is correlated with taste for food consumption. People with a strong preference for a lavish lifestyle might be more motivated to work harder and earn higher incomes. They may also have a jaded palate and choose to consume a more restrictive range of foods. However, the sign of the omitted variable bias in this case is not clear. It depends on (i) the sign of the coefficient of the omitted variable in the true model, and (ii) the correlation between the omitted variable and the remaining variables in the estimated model[6].

Assuming the absence of mutual causality, the OLS estimated income effect is conditional on only observed variables included in the model. That estimate captures both the "true" income effect, which influences diet diversity solely through higher purchasing power, and indirect effects through income of omitted factors that correlate with income. In this sense, the "true" income effect is the effect often expected from income-based policies, such as cash transfer schemes or food coupons. Such programs effectively increase the disposable income of the

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[6] Wooldridge (2006) provides a useful discussion on the omitted variable bias in two simple cases, where the estimated model has only one and two regressors, respectively (pp. 95-99). Suppose the true model is
$$y = \hat{\beta}_1.x_1 + \hat{\beta}_2.x_2 + \cdots + \hat{\beta}_{k-1}.x_{k-1} + \hat{\beta}_k.x_k + \varepsilon \quad (3)$$
yet the estimated model omit x_k:
$$y = \tilde{\beta}_1.x_1 + \tilde{\beta}_2.x_2 + \cdots + \tilde{\beta}_{k-1}.x_{k-1} + v \quad (4)$$
It is easy to see that $\tilde{\beta}_i = \hat{\beta}_i + \hat{\beta}_k.\gamma_i$ where γ_i is the estimated coefficient of x_i in the auxiliary regression of x_k on x_1, $x_2, \dots x_{k-1}$. The omitted variable bias will be $\hat{\beta}_k.\gamma_i$ (*i=1, 2, …, k-1*)

targeted population, while keeping all other factors constant. From a policy maker's point of view, therefore, it is more important to know the marginal effect of income that is conditional on both observed and unobserved variables. The OLS estimates, unfortunately, fails to distinguish the "true" income effect and the indirect effect of unobserved variables.

In the presence of endogeneity, OLS estimator of equation (1) will be inconsistent and biased. Thus, even though the existence of endogeneity of income is controversial, it deserves to be addressed. As far as the author knows, this study is the first to do so by using instruments for household income and estimate equation (1) by 2SLS method. The existence of endogeneity will be formally tested. Estimates from OLS and 2SLS methods will be compared in later sections.

The choice of a valid instrument is always a complicated task. Ideally, we want an instrumental variable that is correlated with household income per capita but not with diet variety or unobserved factors that influence diet variety. The literature on income effects on dietary intakes has used a wide variety of instruments for household income or expenditure. Examples include but are not limited to non-labor income, factors associated with permanent income such as farm size, schooling of household head (Behrman & Deolalikar 1987), non-food expenditure and count of household assets (Skoufias *et al.* 2009), and rainfall (Behrman & Deolalikar 1987; Mangyo 2008).

Given the available data in the CHNS, this study uses count of household durable assets and tries 3 different sets of instruments for household income per capita. The first set (IV1) is only the total number of durable assets owned by the household. The second one (IV2) includes the numbers of car, color TV, fan, and computer, individually. The third set (IV3) consists of the numbers of car, microwave, and camera[7], individually. The stock of durables is effectively a measure of wealth and is informative about household income. In a static model current productivity and/or labor supply should be unaffected by wealth, so it may be a valid instrument (Strauss & Thomas 1995). A priori this study assumes that the only possible link between stock of durables and diet variety is through income, i.e. there is no causal relationship between number of durable assets and how diversified household members' food consumption is. This implicitly means we reject the possibility that there is any correlation through substitution effect between food expenditure and durable asset expenditures. The two later sets of instruments over-identify the model, and thus, their validity can be formally tested. The issue of weak instrument will also be statistically tested at a later stage.

The first stage equation is specified as follow:

$$\log{(income)}_{ijk} = \gamma_1 + \gamma_2.IV_{ijk} + \gamma_3.food_{ijk} + \gamma_4.I_{ijk} + \gamma_5.H_{jk} + \gamma_6.C_k + v_{ijk} \qquad (2)$$

where IV_{ijk} is the vector of instruments for household j in community k, $food_{ik}$, I_{ik}, H_{jk}, C_k are the same set of exogenous variables used in the main estimating equation (1), v_{ijk} is the individual specific error that could reflect unobserved tastes or consumption habits.

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[7] IV3 was selected after a process of trial and error to find a set of instruments that pass the validity test for all 3 examined years.

2SLS regression on equation (1) using equation (2) as the first-stage equation provides a consistent estimator, as long as the chosen instruments and ε_{ijk} are not correlated. The 2SLS estimation is conducted by the command *ivregress*[8] *2sls* with option *vce(robust)* to correct for heteroskedasticity.

The statistical preference toward a semi-log relationship between income and diet variety, as suggested by the OLS analysis, serves as a reference point to conduct the 2SLS estimation. Starting with model 3, log of real household income per capita is instrumented by the three aforementioned sets of instruments. The study will consequently compare the 2SLS estimates with their counterparts from model 3.

5.2 First stage regression results – Instruments' validity and relevance

For brevity, the full first stage regression is shown in Appendix 3. Table 9 below contains results of the validity test whenever the endogenous variable is over-identified, the Durbin-Wu-Hausman test of endogeneity, and tests of weak instruments, respectively.

Table 8: First-stage regression statistics

	IV 1			IV 2			IV 3		
	2004	2006	2009	2004	2006	2009	2004	2006	2009
Validity									
χ^2	na.	na.	na.	2.77	5.52	1.56	3.27	0.387	0.23
p-value	na.	na.	na.	0.428	0.137	0.669	0.195	0.824	0.890
Endogeneity									
F-value	54.9	28.8	19.3	17.4	17.6	57.4	57.6	1.88	59.8
prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.171	0.000
Relevance									
F-stat for IV	537.6	406.8	338.7	56.3	51.6	61.0	78.2	45.7	74.0
prob >F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.304	0.272	0.202	0.265	0.232	0.184	0.260	0.219	0.183
Partial R^2	0.095	0.091	0.069	0.048	0.044	0.049	0.042	0.031	0.046
Critical value for 5% size distortion of Wald test	16.4	16.4	16.4	24.6	24.6	24.6	22.30	22.30	22.30

Validity

The essential condition for consistency of IV estimates is that instruments are uncorrelated with the error term ε_{ijk} in equation (1). Although no test is possible in the just-identified case, the Hansen-Sargen[9] test can check the validity of the two over-identifying instruments, IV2 and IV3.

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[8] As noted in Cameron and Trivedi (p. 183, 2010), *ivregress* is the updated and significantly enhanced version of *ivreg* and incorporates several features of the user-written *ivreg2* command.

[9] The starting point of the test is the fitted value of the objective function after optimal GMM:

$$Q(\hat{\beta}) = \left[\frac{1}{N}\ (y - X\hat{\beta})'Z\right] . \hat{S}^{-1} . [\frac{1}{N}\ Z'(y - X\beta)]$$

which is a matrix-weighted quadratic form in $Z'(y - X\beta)$, where S is an estimate of $Var(N^{-\frac{1}{2}}Z'\varepsilon)$, Z is the vector of instruments, y is the dependent variable and X is the vector of explanatory variables and parameters (Cameron & Trivedi 2010, p.191). Under the null hypothesis that all instruments are valid, $Q(\hat{\beta})$ has an asymptotic χ^2 distribution

As displayed in the second panel of Table 9, the test statistics (χ^2) fails to reject the null hypothesis that all instruments are valid even at 10% significance level in all cases. This appears to exclude the possible problem of invalid instruments[10].

Endogeneity

Providing that the chosen instruments are valid, the Durbin-Wu-Hausman (DHW) test formally verifies the existence of endogeneity in equation (1). The test results strongly reject the null hypothesis that income is exogenous (p-value=0.000 in almost all cases, except in 2006 under IV3). These test results render the OLS estimates presented in previous section biased and inconsistent. They also suggest a case for using instruments for household income in order to obtain consistent estimated coefficients in equation (1).

Relevance

Although IV estimators are consistent given valid instruments, they can be much less efficient than the OLS estimators and have finite-sample distribution that differs drastically from the asymptotic distribution. Weak instruments, loosely defined as those weakly correlated with the instrumented variable, greatly magnify these problems (Cameron & Trivedi 2009, p. 103).

This study investigates the concern for weak instruments through several measures. First, the first-stage estimation shows that all the chosen instruments, as expected, have a positive and significant relationship with household income. The gross correlations of instruments with income, presented in Table 10, are relatively low. This might lead to substantial efficiency loss in 2SLS estimation as compared to OLS estimation. But the correlations are not so low as to immediately flag a problem of weak instruments.

Table 9: Correlation of endogenous variable with instruments

Correlation with log of real household income per capita	2004	2006	2009
Total number of durable assets	0.388	0.315	0.235
No. of cars	0.081	0.074	0.099
No. of color TVs	0.241	0.186	0.103
No. of fan	0.088	0.008	0.021
No. of microwaves	0.352	0.286	0.280
No. of computers	0.194	0.232	0.231

Another diagnostic measure is the F statistic for the joint significance of the instruments in the first-stage regression. These F-values, displayed in the last panel of Table 9, are all considerably larger than 10, a widely used threshold suggested by Staiger and Stock (1997) that indicates weak instruments. Cameron and Trivedi (2010), however, warn that this rule of thumb is ad-hoc

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with degrees of freedom equal to the number of over-identifying restrictions. Rejection of the null hypothesis, thus, is interpreted as indicating that at least one of the instruments is invalid.

[10] As noted in Cameron and Trivedi (2010), failure to reject the null hypothesis in the Hansen-Sargen test can have power in directions other than guaranteeing that all instruments are valid. It is possible that rejection "indicates that the model $X\beta$ for the conditional mean is mis-specified" (p.191).

and may not be sufficiently conservative when there are many over-identifying restrictions (p.196). To be prudent, this study follows the procedure proposed by Stock and Yogo (2002) and formally tests the null hypothesis that the instruments are weak against the alternative that they are strong. Stock and Yogo's test addresses the concern that weak instruments can lead to size distortion of the Wald test on the significance of the endogenous regressor in equation (1) in finite samples. With only one endogenous variable, the test statistic is the aforementioned F statistic for the joint significance of instruments in the first-stage regression. As can be seen in the last panel of Table 9, all F values are well above the critical values for a 5% maximal size distortion, thus, strongly rejecting the null hypothesis. These measures thus suggest that weak instrument problem is negligible in the present estimation.

5.3 2SLS estimates: Income effects

Table 10: 2SLS estimated income coefficients

Model	Variable	2004	2006	2009
3 (OLS)	Log of income	0.090***	0.067***	0.039***
5 (IV1)	Log of income	0.587***	0.277***	0.386***
6 (IV2)	Log of income	0.623***	0.233***	0.382***
7 (IV3)	Log of income	0.501***	0.137***	0.384***
* p < 0.10, ** p < 0.05, *** p < 0.01				

The first panel of Table 11 above presents OLS estimated coefficients of log of income, the second 2SLS estimates using the three sets of instruments, respectively. The most striking pattern arising is that the 2SLS estimated income effects are considerably larger than the corresponding OLS estimates. The estimated coefficients under IV1 are approximately 6.5, 4.1, and 10.0 times higher than their OLS counterparts in 2004, 2006, and 2009, respectively.

Since this is the first time income is instrumented in modelling the relationship between income and diet diversity, there is no existing results to compare how much estimated coefficients of income would change between OLS and 2SLS methods. The literature, however, does provide some relative reference points. Variyam *et al.* (1998), for example, account for the endogeneity of nutrition information variables when estimating their impacts on diet quality in the US. Their estimated coefficients of both nutrient content knowledge and diet-health awareness under 2SLS is about 6.4 times higher than corresponding OLS estimates (p. 12). In a related study by Skoufias *et al.* (2009), household income is instrumented by number of household assets[11]. Their income elasticity of nutrient intakes display assorted changes between OLS and 2SLS methods. The elasticity for energy intake drops from 0.44 to 0.101, for protein intake from 0.495 to -0.058 and becomes insignificant. In contrast, the income elasticity of vitamin A remains roughly the same at 1.259 and 1.202. Meanwhile, elasticity of calcium intake increases from 0.78 to 0.96. These existing results, though not directly compatible with the present findings, indicate that

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[11] Skoufias *et al.* also use non-food expenditure and locality median of per capita expenditure as instrument variables for income. For better compatibility, however, this present study only considers their estimates under OLS and 2SLS using number of household assets.

changes of estimated coefficients between OLS and 2SLS methods could be in any direction and magnitude.

The increase in size of the estimated income effect under 2SLS appears to relate to the diminishing of education effect under 2SLS, as shown in Table 13. The 2SLS education coefficients are much smaller than their OLS counterparts; and education attainment levels are jointly insignificant at 10% confidence level in 2009. At the same time, the first-stage estimates in Appendix 3 show that education has a highly significant and positive association with income. This partial correlation between income and education might be an explanation for the changes of income effects between OLS and 2SLS methods. Due to this positive correlation, part of the income effects was falsely attributed to education under OLS or much of the education effect on diet variety occurs indirectly through income.

Another possible explanation is omitted variable bias. Many unobserved factors could influence food choices and diet variety, such as taste, physical activity level, health condition, and consumer's perception about the social image that their foods project. For example, rich people might prefer to consume more expensive foods to prove their social status. It is also possible that taste for work and lifestyle is correlated with taste for food consumption. People with a strong preference for a lavish lifestyle might be more motivated to work harder and earn higher incomes. They may also be pickier about their diets and choose to consume a more restrictive range of foods. However, the sign of the omitted variable bias in this case is not clear. It depends on (i) the sign of the coefficient of the omitted variable in the true model, and (ii) the correlation between the omitted variable and the remaining variables in the estimated model. Suppose a preference for food diversity has a positive coefficient in the true model, its partial correlation with income and education cause OLS estimated income effect to be biased downward, yet estimated education effect upward.

Keep in mind that, under endogeneity, OLS estimates of income effect are biased and inconsistent, though they fit initial expectation of a positive relationship. The much stronger income effect under 2SLS method not only reassures but also re-emphasizes the potentials of income-based policies in improving health through diversity of food consumption, especially among low-income people.

Table 11: Estimated marginal impact of 1000 addition Yuan at mean income

	2004	2006	2009
At	**Estimated increase in diet diversity**		
Sample mean income	1.83%	0.70%	0.67%
Mean income of quintile 1	13.77%	5.47%	6.58%
Mean income of quintile 2	4.51%	1.93%	1.60%
Mean income of quintile 3	2.59%	1.05%	0.96%
Mean income of quintile 4	1.52%	0.62%	0.59%
Mean income of quintile 5	0.65%	0.24%	0.24%
Estimated increase in diet diversity when income doubles, as percentage of sample mean diet diversity	16.67%	7.53%	10.03%

Setting aside the above difference, 2SLS estimates still follow two patterns observed in OLS estimated results. First, income effect is consistently stronger among low income groups. As can be seen in Table 12, marginal effect of 1000 additional Yuan at mean income of quintile 1 is roughly 3 times higher than that of quintile 2, and more than 4 times higher than that of quintile 3. Second, the effect fades away over time. Figure 4 further illustrates both of these patterns. The hierarchical positions of the three curves demonstrate the decline over time of income effect, especially between 2004 and 2006. The curvature also indicates that when a certain income threshold is achieved, the effect flats out. Combining with Table 12, it seems income effect starts to flat out at around the 20th percentile in 2004, while it already does so at around the 10th percentile in 2006 and 2009.

Figure 4: 2SLS estimated marginal impact of 1000 additional Yuan
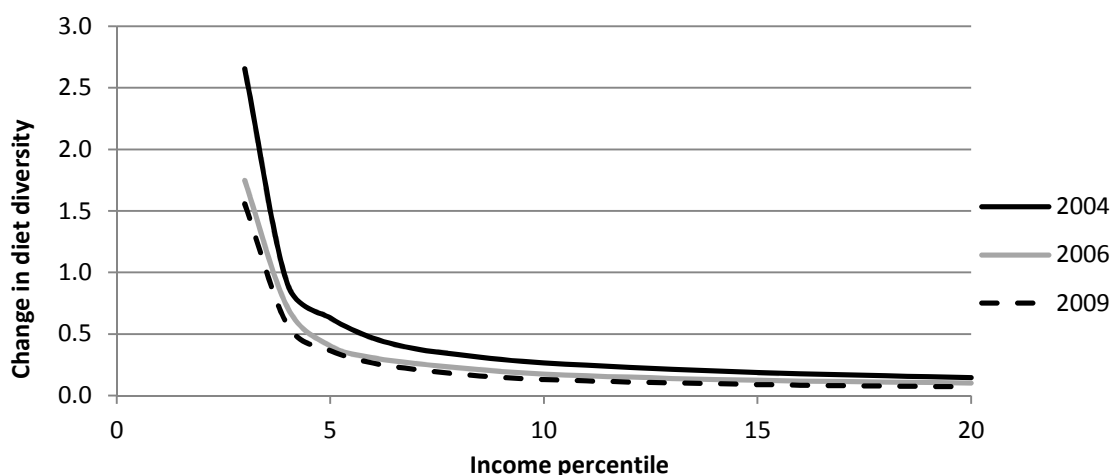
5.4 2SLS estimates: Education effects

OLS and 2SLS estimations do not differ only in estimated income coefficients, but also in estimated education effects. OLS estimation of model3 shows a clear monotonic pattern of education coefficients, with larger effects for higher education attainments. Although this pattern is still largely maintained when income is treated as endogenous, the 2SLS estimated education coefficients are remarkably smaller than their OLS counterparts, as displayed in Table 13.

This decrease in education effects between OLS and 2SLS, though seemingly surprising, is not unheard of. Variyam *et al.* (1998), in their OLS estimation, find the same monotonic increasing pattern of education effects on diet quality, measured by the Healthy Eating Index (p. 12). Nevertheless, when nutrition information variables are instrumented in their 2SLS estimation, most estimated effects of education are insignificant and do not correspond to the categorical order of education attainments. Variyam *et al.*'s first-stage regression also shows education to have a significant, positive, and increasing effect on the endogenous variables.

Table 12: 2SLS estimated education coefficients

Model	Education level	2004	2006	2009
		OLS		
	Primary	0.122***	0.026	0.113***
	Secondary	0.258***	0.192***	0.165***
3	High school	0.398***	0.300***	0.255***
	Vocational training	0.587***	0.492***	0.387***
	University & above	0.572***	0.398***	0.405***
	p-value for education restrictions	p=0.000	p=0.000	p=0.000
		2SLS		
	Primary	0.076*	0.006	0.042
	Secondary	0.140***	0.140***	0.056
5 (IV1)	High school	0.186***	0.218***	0.062
	Vocational training	0.213***	0.343***	0.145**
	University & above	0.078	0.120***	0.077
	F-stat for education restrictions	0.000	0.000	0.281
	Primary	0.073	0.010	0.042
	Secondary	0.132***	0.151***	0.057
6 (IV2)	High school	0.171***	0.235***	0.064
	Vocational training	0.185**	0.374***	0.148**
	University & above	0.043	0.241***	0.080
	F-stat for education restrictions	0.002	0.000	0.307
	Primary	0.084**	0.019	0.042
	Secondary	0.161***	0.175***	0.057
7 (IV3)	High school	0.223***	0.273***	0.063
	Vocational training	0.277***	0.443***	0.147**
	University & above	0.164*	0.333***	0.079
	F-stat for education restrictions	0.000	0.000	0.304

As discussed in the previous subsection, omitted variable bias could be a cause of education effect's disappearance. The positive link between education and omitted factors that have an increasing relationship with diet diversity causes OLS estimated education effect biased upward.

This phenomenon could also be explained, at least partly, by the steadily increasing effects of higher education on income in the first-stage regression. Higher education might provide greater access to information and higher information process efficiency, thus directly influencing healthy food choices. At the same time, higher education of an individual may either result in higher household income or be a result of higher household income. The present results suggest that

OLS estimates falsely attribute part of income effects to education, and that the role of education in determining diet diversity appears to be mostly indirect and income-related.

5.5 2SLS estimates: Effects of demographic factors

Table 134: OLS and 2SLS estimated coefficients of demographics

Model	Variables	2004	2006	2009
			OLS	
3	Female	0.116***	0.177***	0.152***
	Age	-0.002	-0.009	-0.005
	Age squared (divided by 100)	0.004	0.012	0.005
	Household size (adult equivalent)	0.038***	0.026**	0.035**
			2SLS	
5 (IV1)	Female	0.113***	0.180***	0.152***
	Age	0.005	-0.013*	-0.007
	Age squared (divided by 100)	-0.007	0.017**	0.007
	Household size (adult equivalent)	0.0428***	0.018	0.035**
6 (IV2)	Female	0.114***	0.177***	0.153***
	Age	0.005	-0.012*	-0.007
	Age squared (divided by 100)	-0.008	0.016*	0.007
	Household size (adult equivalent)	0.027*	0.021	0.034**
7 (IV3)	Female	0.122***	0.186***	0.152***
	Age	0.004	-0.010	-0.007
	Age squared (divided by 100)	-0.005	0.014*	0.007
	Household size (adult equivalent)	0.027*	0.001	0.035**

The estimated effects of gender, age, and household size are consistently between the two estimation methods. Under OLS, daily diet of a female tends to have approximately 0.12-0.18 more food groups than that of a male. The impact of being a female persists under 2SLS, as evidenced by similar estimates of 0.11-0.19. Likewise, age is expected to have a convex yet insignificant association with diet diversity under both OLS and 2SLS, with roughly similar estimated coefficients. On the contrary, the coefficient of household size changes noticeably between OLS and 2SLS. OLS estimation shows that household size is significant in explaining diet diversity of an individual. Having one extra household member in adult equivalence scale increases diet variety by around 0.03-0.04 food groups. Under 2SLS, the coefficient of household size remains positive with similar magnitude. Although the coefficient becomes insignificant in 2006, this change is negligible. 2SLS estimates usually have larger standard deviation than OLS estimates due to efficiency loss. Given similar point estimates, larger standard deviation reduces the t-statistics and might render the estimates statistically insignificant.

5.6 2SLS estimates: Effects of community factors

Table 145: OLS and 2SLS estimated coefficients of province dummies

Model	Province	2004	2006	2009
		OLS		
	Heilongjiang	-0.481***	-0.251***	-0.457***
	Jiangsu	-0.054	-0.082*	-0.507***
	Shandong	-0.159***	-0.355***	-0.295***
3	Henan	-0.399***	-0.568***	-0.672***
	Hubei	-0.379***	-0.604***	-0.727***
	Hunan	-0.289***	-0.254***	-0.633***
	Guangxi	-0.577***	-0.667***	-0.569***
	Guizhou	-0.253***	-0.233***	-0.558***
		2SLS		
	Heilongjiang	-0.494***	-0.177***	-0.492***
	Jiangsu	-0.346***	-0.128***	-0.637***
	Shandong	-0.177***	-0.339***	-0.360***
5 (IV1)	Henan	-0.311***	-0.520***	-0.575***
	Hubei	-0.263***	-0.505***	-0.709***
	Hunan	-0.118*	-0.129**	-0.627***
	Guangxi	-0.562***	-0.549***	-0.507***
	Guizhou	-0.088	-0.161***	-0.542***
	Heilongjiang	-0.495***	-0.192***	-0.492***
	Jiangsu	-0.367***	-0.119**	-0.636***
	Shandong	-0.178***	-0.342***	-0.360***
6 (IV2)	Henan	-0.305***	-0.530***	-0.576***
	Hubei	-0.255***	-0.526***	-0.709***
	Hunan	-0.106	-0.155**	-0.627***
	Guangxi	-0.561***	-0.573***	-0.509***
	Guizhou	-0.076	-0.176***	-0.542***
	Heilongjiang	-0.492***	-0.226***	-0.492***
	Jiangsu	-0.296***	-0.097**	-0.636***
	Shandong	-0.174***	-0.350***	-0.360***
7 (IV3)	Henan	-0.326***	-0.552***	-0.575***
	Hubei	-0.284***	-0.571***	-0.709***
	Hunan	-0.148**	-0.213***	-0.627***
	Guangxi	-0.565***	-0.628***	-0.508***
	Guizhou	-0.116*	-0.209***	-0.542***

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Table 156: OLS and 2SLS estimated rural effects

Model	2004	2006	2009
	OLS		
3	-0.356***	-0.195***	-0.251***
	2SLS		
5	-0.227***	-0.166***	-0.220***
6	-0.218***	-0.172***	-0.220***
7	-0.250***	-0.186***	-0.220***
* p < 0.10, ** p < 0.05, *** p < 0.01			

Regional effects from the 2SLS estimation are in the same line with corresponding OLS estimates in terms of sign, magnitude, and the pattern of changes overtime. Residents in Liaoning still have a greater diet variety than those in other sampled provinces. However, the relative differences among provinces are not robust between the two estimation methods and remain puzzle.

Living in a rural area consistently imposes a penalty on diet variety as compared to living in an urban area. The robustness of rural effects between the two estimation methods and across surveyed years stresses the importance of regional fixed effects. The difference between residential areas, thus, might help identify social sub-groups who are subject to bad diet and should be targeted in food and health programs.

Separate regressions by urban and rural areas show that income effect is considerably stronger in rural area, as can be seen in Table 17. This might be due to income inequality between urban and rural areas. The rural residents on average have lower incomes than their urban counterparts. They, thus, lie on the steeper section of the concave relationship between income and diet diversity, where income effect is stronger. On the other hand, schooling education has stronger effects among urban residents.

Table 167: 2SLS estimated income and education effects by urban and rural

Model	Variable	2004		2006		2009	
		Rural	Urban	Rural	Urban	Rural	Urban
5 (IV1)	Log of income	0.7070***	0.4609***	0.3703***	0.2477***	0.4094***	0.2895***
	Primary	0.0799	0.1518*	-0.0038	0.0139	0.0358	0.0963
	Secondary	0.1403**	0.1903**	0.0901**	0.2045***	0.0262	0.1286*
	High school	0.1631**	0.2211***	0.1628***	0.2078***	0.0369	0.1581*
	Vocational training	0.2470***	0.2365***	0.3314***	0.3185***	0.1531*	0.2011**
	University & above	0.1603	0.0940	0.1180	0.2247**	0.1088	0.2422**
6 (IV2)	Log of income	0.7233***	0.5099***	0.2765***	0.2285***	0.2675***	0.2668***
	Primary	0.0736	0.1327*	0.0083	0.0157	0.0485	0.1212
	Secondary	0.1258**	0.1809**	0.1084**	0.2057***	0.0686	0.1518**
	High school	0.1457**	0.2021**	0.1962***	0.2181***	0.0954*	0.1940**
	Vocational training	0.2280**	0.2080**	0.3860***	0.3301***	0.2263***	0.2353**
	University & above	0.1245	0.0534	0.2074*	0.2458**	0.1696*	0.2843**
7 (IV3)	Log of income	0.5907***	0.5070***	0.1302**	0.2462***	0.2555***	0.3414***
	Primary	0.0808	0.1306	0.0225	0.0136	0.0528	0.0997
	Secondary	0.1612***	0.1815**	0.1367***	0.1981***	0.0755	0.1273
	High school	0.1957***	0.2080**	0.2514***	0.2083***	0.1040*	0.1377
	Vocational training	0.3349***	0.2110**	0.4868***	0.3125***	0.2358***	0.1686*
	University & above	0.2530*	0.0585	0.3460***	0.2276**	0.1932**	0.1945*

* p < 0.10, ** p < 0.05, *** p < 0.01

VI.   Conclusion

Recent empirical literature on nutrition intakes and income in China suggests that income growth either plays a small or even a negative role in influencing diet quality in China, especially for low income households. Such arguments cast doubt on the conventional reliance on income as a policy tool to improve dietary consumption and tackle diet-related health issues. They, however, have been drawn mostly from analysis of changes in level of nutrient intakes and income effects on diet adequacy. Diet adequacy, however, is only one of several aspects of diet quality. On the one hand, the existing evidence on increasing consumption of high-fat diets and continued deficiencies of some micronutrients as income rises remains relevant and important. On the other hand, they should not be over-generalized into a conclusion that overall diet quality deteriorates when household income increases.

This study sheds new light on the current prospect of worsening diet quality and increasing risks of diet-related diseases in China. It explores the influence of household income on diet variety, an essential yet understudied aspect of diet quality. No matter which model specifications and estimation methods are adopted, the estimation results show that higher income improves diet variety. When endogeneity of income is controlled for, estimated income effect increases about

seven times. Income growth, hence, can at least partly offset harmful effects of the nutrition transition on labor health. The current results also complement previous findings that income positively affects diet diversity. More importantly, the income effect is found to be diminishing along the income distribution. Low-income people, particularly those in the poorest quintile, will benefit the most when household income increases. Their mean diet diversity is expected to increase by around 5.5%-13.8% if their annual household income per capita rises by 1000 Yuan. Together, these findings provide some reassurance that income growth remains important in driving up dietary welfare amid the structural shift in nutrition intakes in China. Income-based policies that aim to improve diet quality should target the poor, who are more vulnerable yet will receive larger marginal benefit from income growth.

A somewhat surprising but critical finding is the small role of education in determining diet variety. Simple OLS regression shows that education has a significant and positive effect on diet diversity, with larger effect at higher education levels. However, when the endogeneity between income and the dependent variable is addressed by 2SLS estimation, education effects diminish in terms of both statistical significance and magnitude.

This research has placed a special focus on isolating true income effect (through higher purchasing power) from indirect impacts of various omitted factors that associate with both income and diet diversity through the 2SLS estimation. The stark difference between OLS and 2SLS estimates suggests that it is important to detect and address endogeneity in income, which the existing literature has neglected. The OLS approach, as shown in this study, understates the role of income and overstates education effects. Relying on OLS estimates, therefore, might mislead resource allocation in designing food and health policies.

This paper also finds that residential area plays an important role in influencing diet diversity. Urban residents also have a higher diet variety, probably because they might have a wider choice of food thanks to larger food availability. Separate regressions by region also show that the effect of income is stronger in rural areas, yet schooling education has stronger impacts on diversity of food consumption in urban areas. As a result, more attention should be paid to the distinction between urban and rural in designing and targeting policies that aim to tackle nutrition-related issues.

It is important to note that various measures of diet variety have been employed in the literature. Some measures, such as the Berry index and Entropy index, account for the distribution of each consumed food in the total consumption, yet ignore health aspects of the food consumed. Count measures, like the one used in this paper, though ignoring the relative share of each food item, follows the nutrition literature more closely in reflecting the healthiness of a diversified diet. Even among studies using count measures of food diversity, different cut-off points, groupings of food items, and reference periods have been used. This limits generalization and compatibility of the present results with existing empirical evidences. It is desirable to have further research on how such results response to different measures of diversity, and if policy implications change when one switches from one measure to another.

Appendixes

Appendix 1: Map of surveyed provinces

Source: Center of Population at the University of North Carolina at Chapel Hill, viewed 1 June 2012, <http://www.cpc.unc.edu/projects/china/proj_desc/chinamap >.

Appendix 2: OLS estimation results

Model	(1)			(2)			(3)			(4)		
	2004	2006	2009	2004	2006	2009	2004	2006	2009	2004	2006	2009
Heilongjiang	-0.4797***	-0.2709***	-0.4541***	-0.4815***	-0.2525***	-0.4535***	-0.4883***	-0.2430***	-0.4596***	-0.4806***	-0.2507***	-0.4571***
	(0.0434)	(0.0515)	(0.0464)	(0.0434)	(0.0514)	(0.0464)	(0.0432)	(0.0511)	(0.0465)	(0.0433)	(0.0513)	(0.0463)
Jiangsu	-0.0486	-0.0712	-0.4976***	-0.0645	-0.0782*	-0.5044***	-0.0674	-0.0796*	-0.5169***	-0.0541	-0.0815*	-0.5065***
	(0.0457)	(0.0475)	(0.0405)	(0.0458)	(0.0473)	(0.0405)	(0.0458)	(0.0471)	(0.0407)	(0.0459)	(0.0472)	(0.0404)
Shandong	-0.1540***	-0.3644***	-0.2905***	-0.1516***	-0.3466***	-0.2937***	-0.1562***	-0.3442***	-0.3004***	-0.1591***	-0.3554***	-0.2954***
	(0.0520)	(0.0478)	(0.0423)	(0.0519)	(0.0477)	(0.0423)	(0.0520)	(0.0476)	(0.0425)	(0.0519)	(0.0478)	(0.0422)
Henan	-0.4072***	-0.5831***	-0.6804***	-0.3970***	-0.5764***	-0.6759***	-0.3929***	-0.5611***	-0.6789***	-0.3985***	-0.5678***	-0.6715***
	(0.0517)	(0.0506)	(0.0421)	(0.0516)	(0.0504)	(0.0421)	(0.0516)	(0.0499)	(0.0422)	(0.0517)	(0.0502)	(0.0423)
Hubei	-0.3836***	-0.6391***	-0.7297***	-0.3697***	-0.6069***	-0.7256***	-0.3767***	-0.5701***	-0.7334***	-0.3792***	-0.6037***	-0.7267***
	(0.0463)	(0.0699)	(0.0460)	(0.0463)	(0.0699)	(0.0460)	(0.0461)	(0.0695)	(0.0460)	(0.0462)	(0.0698)	(0.0459)
Hunan	-0.3044***	-0.2907***	-0.6353***	-0.2976***	-0.2636***	-0.6302***	-0.2897***	-0.2357***	-0.6335***	-0.2891***	-0.2536***	-0.6326***
	(0.0480)	(0.0587)	(0.0452)	(0.0480)	(0.0584)	(0.0452)	(0.0479)	(0.0587)	(0.0452)	(0.0480)	(0.0586)	(0.0450)
Guangxi	-0.5754***	-0.7018***	-0.5747***	-0.5760***	-0.6667***	-0.5660***	-0.5829***	-0.6350***	-0.5724***	-0.5771***	-0.6665***	-0.5689***
	(0.0546)	(0.0639)	(0.0605)	(0.0543)	(0.0638)	(0.0607)	(0.0540)	(0.0642)	(0.0609)	(0.0541)	(0.0639)	(0.0606)
Guizhou	-0.2589***	-0.2550***	-0.5601***	-0.2473***	-0.2399***	-0.5566***	-0.2514***	-0.2149***	-0.5659***	-0.2525***	-0.2333***	-0.5582***
	(0.0511)	(0.0490)	(0.0550)	(0.0508)	(0.0487)	(0.0550)	(0.0506)	(0.0487)	(0.0555)	(0.0509)	(0.0487)	(0.0552)
Rural	-0.3558***	-0.2023***	-0.2529***	-0.3451***	-0.1881***	-0.2481***	-0.3432***	-0.1921***	-0.2473***	-0.3560***	-0.1950***	-0.2506***
	(0.0244)	(0.0228)	(0.0242)	(0.0245)	(0.0227)	(0.0243)	(0.0246)	(0.0227)	(0.0243)	(0.0244)	(0.0226)	(0.0242)
Log of real household income per capita										0.0898***	0.0673***	0.0386***
										(0.0136)	(0.0104)	(0.0111)
Real household income per capita	0.0783***	0.0126*	0.0090**	0.1885***	0.0825***	0.0305***						
	(0.0123)	(0.0072)	(0.0044)	(0.0232)	(0.0110)	(0.0089)						
Square of real household income per capita				-0.0222***	-0.0045***	-0.0011***						
				(0.0040)	(0.0006)	(0.0003)						
Income quintile 2							0.0915***	0.1032***	0.0358			
							(0.0355)	(0.0349)	(0.0353)			
Income quintile 3							0.1568***	0.1905***	0.0621*			
							(0.0353)	(0.0328)	(0.0351)			
Income quintile 4							0.2370***	0.2532***	0.0450			
							(0.0354)	(0.0337)	(0.0342)			
Income quintile 5							0.3070***	0.2739***	0.1506***			
							(0.0375)	(0.0350)	(0.0356)			
Primary school	0.1230***	0.0315	0.1186***	0.1185***	0.0238	0.1151***	0.1177***	0.0233	0.1097***	0.1216***	0.0259	0.1133***
	(0.0392)	(0.0378)	(0.0394)	(0.0391)	(0.0376)	(0.0394)	(0.0391)	(0.0375)	(0.0393)	(0.0391)	(0.0376)	(0.0394)
Secondary school	0.2633***	0.2063***	0.1727***	0.2555***	0.1951***	0.1691***	0.2515***	0.1806***	0.1619***	0.2578***	0.1923***	0.1648***

	(0.0380)	(0.0331)	(0.0351)	(0.0379)	(0.0330)	(0.0351)	(0.0379)	(0.0330)	(0.0350)	(0.0380)	(0.0330)	(0.0351)
High school	0.4113***	0.3236***	0.2693***	0.3940***	0.3047***	0.2608***	0.3864***	0.2833***	0.2508***	0.3983***	0.3004***	0.2547***
	(0.0420)	(0.0377)	(0.0396)	(0.0421)	(0.0375)	(0.0397)	(0.0421)	(0.0377)	(0.0396)	(0.0423)	(0.0376)	(0.0397)
Vocational training	0.6037***	0.5311***	0.4063***	0.5819***	0.4941***	0.3963***	0.5693***	0.4680***	0.3806***	0.5870***	0.4919***	0.3868***
	(0.0481)	(0.0449)	(0.0462)	(0.0481)	(0.0450)	(0.0462)	(0.0480)	(0.0450)	(0.0464)	(0.0483)	(0.0450)	(0.0464)
University & higher	0.5807***	0.4454***	0.4296***	0.5534***	0.4097***	0.4119***	0.5529***	0.3768***	0.3916***	0.5715***	0.3984***	0.4050***
	(0.0575)	(0.0498)	(0.0504)	(0.0574)	(0.0499)	(0.0508)	(0.0570)	(0.0507)	(0.0512)	(0.0575)	(0.0505)	(0.0508)
Age	-0.0024	-0.0074	-0.0047	-0.0022	-0.0076	-0.0047	-0.0026	-0.0087	-0.0055	-0.0020	-0.0085	-0.0049
	(0.0068)	(0.0069)	(0.0069)	(0.0069)	(0.0068)	(0.0069)	(0.0069)	(0.0068)	(0.0069)	(0.0069)	(0.0068)	(0.0069)
Age squared (divided by 100)	0.0049	0.0110	0.0048	0.0046	0.0111	0.0048	0.0049	0.0126	0.0056	0.0041	0.0124	0.0049
	(0.0084)	(0.0083)	(0.0084)	(0.0084)	(0.0083)	(0.0084)	(0.0084)	(0.0082)	(0.0084)	(0.0084)	(0.0083)	(0.0084)
Female	0.1524***	0.1932***	0.1719***	0.1498***	0.1913***	0.1712***	0.1475***	0.1891***	0.1705***	0.1497***	0.1899***	0.1704***
	(0.0204)	(0.0203)	(0.0207)	(0.0204)	(0.0203)	(0.0207)	(0.0203)	(0.0202)	(0.0207)	(0.0204)	(0.0203)	(0.0207)
Food consumption	0.5042***	0.6876***	0.5837***	0.4979***	0.6758***	0.5798***	0.4929***	0.6631***	0.5760***	0.4970***	0.6698***	0.5768***
	(0.0296)	(0.0271)	(0.0298)	(0.0296)	(0.0272)	(0.0298)	(0.0296)	(0.0272)	(0.0298)	(0.0296)	(0.0272)	(0.0298)
Household size (adult equivalent)	-0.0292**	-0.0221**	-0.0281**	-0.0260**	-0.0148	-0.0252**	-0.0238**	-0.0088	-0.0211*	-0.0274**	-0.0122	-0.0245**
	(0.0117)	(0.0110)	(0.0115)	(0.0117)	(0.0110)	(0.0116)	(0.0117)	(0.0110)	(0.0116)	(0.0117)	(0.0110)	(0.0115)
Rice price	-0.0015	0.3499***	-0.0674	0.0014	0.3212***	-0.0643	-0.0006	0.3243***	-0.0614	0.0025	0.3305***	-0.0623
	(0.0332)	(0.0661)	(0.0516)	(0.0330)	(0.0657)	(0.0515)	(0.0330)	(0.0653)	(0.0516)	(0.0329)	(0.0654)	(0.0513)
Pork price	-0.0374	-0.0220	0.1889***	-0.0337	-0.0269	0.1860***	-0.0257	-0.0302	0.1830***	-0.0283	-0.0243	0.1848***
	(0.0284)	(0.0307)	(0.0426)	(0.0283)	(0.0305)	(0.0427)	(0.0286)	(0.0304)	(0.0429)	(0.0284)	(0.0305)	(0.0427)
Fish price	-0.1013***	-0.3035***	-0.1512***	-0.0941***	-0.2871***	-0.1489***	-0.0889**	-0.2955***	-0.1461***	-0.0913**	-0.3036***	-0.1428***
	(0.0358)	(0.0537)	(0.0470)	(0.0360)	(0.0532)	(0.0470)	(0.0365)	(0.0532)	(0.0471)	(0.0363)	(0.0534)	(0.0472)
Cabbage price	0.0513***	-0.0043	0.1301***	0.0481***	-0.0038	0.1276***	0.0452***	-0.0073	0.1246***	0.0476***	-0.0054	0.1269***
	(0.0143)	(0.0177)	(0.0206)	(0.0143)	(0.0177)	(0.0206)	(0.0143)	(0.0177)	(0.0206)	(0.0143)	(0.0177)	(0.0206)
Tofu price	-0.1420***	-0.0296	-0.1391***	-0.1382***	-0.0337	-0.1403***	-0.1313***	-0.0135	-0.1391***	-0.1347***	-0.0281	-0.1382***
	(0.0251)	(0.0296)	(0.0308)	(0.0253)	(0.0295)	(0.0308)	(0.0252)	(0.0293)	(0.0309)	(0.0252)	(0.0294)	(0.0308)
Apple price	0.0665**	0.0401	0.1413***	0.0659**	0.0149	0.1407***	0.0687**	0.0035	0.1458***	0.0630**	0.0141	0.1416***
	(0.0316)	(0.0463)	(0.0379)	(0.0315)	(0.0463)	(0.0379)	(0.0315)	(0.0462)	(0.0379)	(0.0315)	(0.0461)	(0.0378)
Soy oil price	0.2755***	0.1320***	0.2809***	0.2723***	0.1312***	0.2780***	0.2631***	0.1284***	0.2773***	0.2633***	0.1322***	0.2830***
	(0.0377)	(0.0274)	(0.0413)	(0.0374)	(0.0273)	(0.0413)	(0.0373)	(0.0271)	(0.0413)	(0.0375)	(0.0272)	(0.0412)
Constant	3.1689***	3.4150***	3.2393***	3.0802***	3.3526***	3.2187***	3.0469***	3.2873***	3.2167***	2.4347***	2.8671***	2.8973***
	(0.1775)	(0.1798)	(0.2104)	(0.1777)	(0.1790)	(0.2106)	(0.1795)	(0.1798)	(0.2132)	(0.2104)	(0.2021)	(0.2361)
N	5182	4970	5010	5182	4970	5010	5182	4969	5006	5182	4970	5010
R-sq	0.281	0.302	0.228	0.286	0.308	0.229	0.287	0.313	0.231	0.284	0.308	0.230
Adj. R-sq	0.278	0.298	0.224	0.282	0.304	0.225	0.283	0.308	0.227	0.280	0.304	0.226
AIC	11,053	10,361	10,667	11,026	10,317	10,662	11,016	10,286	10,647	11,034	10,318	10,657
BIC	11,237	10,544	10,850	11,216	10,505	10,851	11,219	10,488	10,849	11,217	10,500	10,839
RMSE	0.7011	0.6843	0.6997	0.6992	0.6812	0.6993	0.6984	0.6791	0.6986	0.6998	0.6813	0.6989

Standard errors in parentheses,   * p<0.10, ** p<0.05, *** p<0.01

Appendix 3: First-stage regression results

	IV 1			IV 2			IV 3		
	2004	2006	2009	2004	2006	2009	2004	2006	2009
Asset	0.0653***	0.0722***	0.0594***						
	(0.0031)	(0.0040)	(0.0032)						
Car				0.2272***	0.2008**	0.2206***	0.2416***	0.2600***	0.2223***
				(0.0416)	(0.0937)	(0.0662)	(0.0445)	(0.0905)	(0.0650)
Color TV				0.1830***	0.2442***	0.0984***			
				(0.0217)	(0.0261)	(0.0201)			
Computer				0.1537***	0.2672***	0.2247***	0.1111***	0.2599***	0.2047***
				(0.0372)	(0.0361)	(0.0255)	(0.0377)	(0.0366)	(0.0252)
Fan				0.0622***	0.0206	0.0682***			
				(0.0106)	(0.0136)	(0.0106)			
Microwave							0.4200***	0.2521***	0.3120***
							(0.0328)	(0.0380)	(0.0350)
Heilongjiang	0.0949*	-0.2360***	0.1844***	0.0685	-0.2722***	0.1434***	0.0480	-0.2974***	0.1458***
	(0.0511)	(0.0568)	(0.0548)	(0.0522)	(0.0580)	(0.0552)	(0.0521)	(0.0583)	(0.0550)
Jiangsu	0.2486***	-0.0736	0.0162	0.4132***	0.1630**	0.1146**	0.4626***	0.1730***	0.1970***
	(0.0511)	(0.0612)	(0.0569)	(0.0556)	(0.0669)	(0.0576)	(0.0502)	(0.0598)	(0.0549)
Shandong	-0.1459**	-0.2054***	-0.0628	-0.0554	-0.0818	0.0151	0.0154	-0.0893	0.0856
	(0.0614)	(0.0674)	(0.0574)	(0.0637)	(0.0701)	(0.0573)	(0.0617)	(0.0680)	(0.0559)
Henan	-0.2716***	-0.2684***	-0.4138***	-0.2541***	-0.1839***	-0.3956***	-0.1627**	-0.2015***	-0.2700***
	(0.0630)	(0.0615)	(0.0600)	(0.0646)	(0.0646)	(0.0617)	(0.0643)	(0.0618)	(0.0591)
Hubei	-0.2791***	-0.4391***	-0.1533**	-0.3041***	-0.4033***	-0.1882***	-0.1848***	-0.3959***	-0.0283
	(0.0531)	(0.1036)	(0.0632)	(0.0589)	(0.1106)	(0.0674)	(0.0548)	(0.1055)	(0.0634)
Hunan	-0.4303***	-0.6075***	-0.1517**	-0.4420***	-0.5263***	-0.1902***	-0.3489***	-0.5271***	-0.0430
	(0.0626)	(0.0845)	(0.0621)	(0.0667)	(0.0936)	(0.0676)	(0.0640)	(0.0872)	(0.0633)
Guangxi	-0.0246	-0.5253***	-0.1984**	-0.0592	-0.5029***	-0.2695***	-0.0177	-0.5593***	-0.0928
	(0.0703)	(0.0843)	(0.0829)	(0.0748)	(0.0890)	(0.0891)	(0.0733)	(0.0851)	(0.0840)
Guizhou	-0.1543***	-0.1676***	0.0358	-0.2698***	-0.2691***	-0.0316	-0.2568***	-0.3089***	0.0051
	(0.0573)	(0.0650)	(0.0833)	(0.0587)	(0.0662)	(0.0843)	(0.0597)	(0.0668)	(0.0840)
Rural	-0.1286***	0.0037	0.0208	-0.1810***	-0.0405	-0.0295	-0.1660***	-0.0433	0.0533
	(0.0300)	(0.0313)	(0.0342)	(0.0307)	(0.0315)	(0.0347)	(0.0310)	(0.0325)	(0.0360)
Primary school	0.0230	0.0356	0.1465***	0.0486	0.0621	0.1725***	0.0636	0.0835	0.1678***
	(0.0429)	(0.0530)	(0.0554)	(0.0438)	(0.0540)	(0.0558)	(0.0445)	(0.0544)	(0.0560)
Secondary school	0.0919**	0.0908*	0.2020***	0.1536***	0.1715***	0.2545***	0.1813***	0.2032***	0.2336***
	(0.0426)	(0.0506)	(0.0495)	(0.0434)	(0.0509)	(0.0497)	(0.0438)	(0.0510)	(0.0500)
High school	0.1883***	0.1491***	0.3628***	0.3018***	0.2748***	0.4440***	0.3170***	0.2916***	0.4046***
	(0.0484)	(0.0547)	(0.0549)	(0.0491)	(0.0554)	(0.0551)	(0.0495)	(0.0558)	(0.0558)

Vocational training	0.4332***	0.3772***	0.4331***	0.5924***	0.5485***	0.5186***	0.5848***	0.5673***	0.4564***
	(0.0519)	(0.0661)	(0.0641)	(0.0521)	(0.0653)	(0.0644)	(0.0520)	(0.0667)	(0.0648)
University & higher	0.6292***	0.5457***	0.6777***	0.8257***	0.7167***	0.7658***	0.7577***	0.7187***	0.6729***
	(0.0594)	(0.0705)	(0.0669)	(0.0593)	(0.0696)	(0.0680)	(0.0600)	(0.0710)	(0.0685)
Age	-0.0165**	0.0213**	0.0107	-0.0098	0.0229**	0.0113	-0.0170**	0.0172*	0.0056
	(0.0081)	(0.0098)	(0.0092)	(0.0084)	(0.0099)	(0.0095)	(0.0084)	(0.0099)	(0.0093)
Age squared (divided by 100)	0.0240**	-0.0272**	-0.0099	0.0165	-0.0283**	-0.0103	0.0259**	-0.0210*	-0.0042
	(0.0099)	(0.0119)	(0.0112)	(0.0101)	(0.0120)	(0.0115)	(0.0102)	(0.0121)	(0.0114)
Female	0.0359	0.0190	0.0304	0.0528**	0.0387	0.0419	0.0520**	0.0402	0.0340
	(0.0249)	(0.0289)	(0.0281)	(0.0255)	(0.0294)	(0.0284)	(0.0256)	(0.0296)	(0.0284)
Food consumption (kg)	0.1049***	0.2573***	0.2056***	0.1258***	0.2741***	0.2263***	0.1127***	0.2832***	0.2230***
	(0.0338)	(0.0331)	(0.0351)	(0.0347)	(0.0334)	(0.0356)	(0.0348)	(0.0339)	(0.0357)
Household size (adult equivalent)	-0.2202***	-0.2878***	-0.2707***	-0.1960***	-0.2400***	-0.2306***	-0.1434***	-0.1896***	-0.1790***
	(0.0149)	(0.0167)	(0.0152)	(0.0155)	(0.0167)	(0.0155)	(0.0146)	(0.0163)	(0.0144)
Rice price	0.0089	0.2640**	-0.2357***	0.0010	0.3091***	-0.2804***	0.0078	0.3230***	-0.2706***
	(0.0466)	(0.1038)	(0.0643)	(0.0479)	(0.1078)	(0.0668)	(0.0484)	(0.1079)	(0.0663)
Pork price	-0.0551*	0.0396	0.0814*	-0.0465	0.0351	0.0962*	-0.0977***	0.0320	0.1030**
	(0.0333)	(0.0445)	(0.0494)	(0.0331)	(0.0455)	(0.0510)	(0.0333)	(0.0453)	(0.0519)
Fish price	-0.2384***	0.2270***	-0.3010***	-0.2313***	0.1607*	-0.2730***	-0.2196***	0.1339	-0.2995***
	(0.0449)	(0.0823)	(0.0612)	(0.0473)	(0.0849)	(0.0617)	(0.0487)	(0.0850)	(0.0621)
Cabbage price	0.0407***	-0.0086	0.0969***	0.0639***	0.0033	0.1106***	0.0714***	0.0075	0.1052***
	(0.0151)	(0.0245)	(0.0254)	(0.0156)	(0.0246)	(0.0257)	(0.0155)	(0.0249)	(0.0258)
Tofu price	-0.0525*	0.0104	-0.0266	-0.0332	-0.0152	-0.0177	-0.0633**	-0.0205	-0.0245
	(0.0282)	(0.0414)	(0.0386)	(0.0288)	(0.0418)	(0.0393)	(0.0292)	(0.0420)	(0.0391)
Apple price	0.1304***	0.4012***	-0.1552***	0.1399***	0.4089***	-0.1218**	0.1329***	0.3970***	-0.1320***
	(0.0376)	(0.0672)	(0.0497)	(0.0390)	(0.0681)	(0.0503)	(0.0386)	(0.0681)	(0.0500)
Soy oil price	0.1381***	-0.0177	0.0548	0.1371***	-0.0107	-0.0109	0.1988***	-0.0096	-0.0339
	(0.0435)	(0.0315)	(0.0589)	(0.0453)	(0.0315)	(0.0594)	(0.0442)	(0.0321)	(0.0601)
Constant	9.3261***	7.7936***	9.1607***	9.2281***	7.8365***	9.2692***	9.4216***	8.0998***	9.4039***
	(0.2111)	(0.2661)	(0.2740)	(0.2174)	(0.2726)	(0.2801)	(0.2169)	(0.2715)	(0.2807)
N	5182	4970	5010	5182	4970	5010	5182	4970	5010
R-sq	0.298	0.260	0.204	0.266	0.232	0.187	0.264	0.223	0.188
adj. R-sq	0.295	0.256	0.200	0.262	0.228	0.182	0.260	0.219	0.184
rmse	0.8295	0.9517	0.9257	0.8485	0.9695	0.9361	0.8497	0.9752	0.9352
F-stat	102.95	72.45	56.13	82.59	59.70	46.81	83.82	57.56	49.04
Prob >F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Appendix 4: 2SLS estimation results

	IV 1			IV 2			IV 3		
	2004	2006	2009	2004	2006	2009	2004	2006	2009
Log of real household income per capita	0.5871***	0.2770***	0.3862***	0.6231***	0.2332***	0.3823***	0.5010***	0.1366***	0.3836***
	(0.0439)	(0.0367)	(0.0441)	(0.0653)	(0.0454)	(0.0541)	(0.0629)	(0.0521)	(0.0548)
Heilongjiang	-0.4941***	-0.1768***	-0.4919***	-0.4951***	-0.1922***	-0.4915***	-0.4918***	-0.2263***	-0.4916***
	(0.0511)	(0.0536)	(0.0501)	(0.0522)	(0.0546)	(0.0501)	(0.0489)	(0.0547)	(0.0503)
Jiangsu	-0.3462***	-0.1287***	-0.6372***	-0.3673***	-0.1188**	-0.6357***	-0.2956***	-0.0971**	-0.6362***
	(0.0565)	(0.0488)	(0.0468)	(0.0645)	(0.0487)	(0.0485)	(0.0609)	(0.0481)	(0.0490)
Shandong	-0.1767***	-0.3388***	-0.3602***	-0.1779***	-0.3423***	-0.3595***	-0.1736***	-0.3499***	-0.3597***
	(0.0596)	(0.0506)	(0.0465)	(0.0608)	(0.0496)	(0.0466)	(0.0571)	(0.0484)	(0.0468)
Henan	-0.3110***	-0.5203***	-0.5746***	-0.3047***	-0.5302***	-0.5756***	-0.3262***	-0.5521***	-0.5753***
	(0.0625)	(0.0517)	(0.0480)	(0.0644)	(0.0517)	(0.0489)	(0.0599)	(0.0516)	(0.0489)
Hubei	-0.2634***	-0.5053***	-0.7091***	-0.2550***	-0.5259***	-0.7093***	-0.2835***	-0.5712***	-0.7092***
	(0.0542)	(0.0753)	(0.0503)	(0.0558)	(0.0753)	(0.0502)	(0.0533)	(0.0754)	(0.0504)
Hunan	-0.1182*	-0.1294**	-0.6273***	-0.1058	-0.1553**	-0.6274***	-0.1478**	-0.2125***	-0.6273***
	(0.0622)	(0.0651)	(0.0488)	(0.0651)	(0.0661)	(0.0488)	(0.0602)	(0.0673)	(0.0488)
Guangxi	-0.5622***	-0.5489***	-0.5080***	-0.5612***	-0.5734***	-0.5087***	-0.5648***	-0.6277***	-0.5084***
	(0.0666)	(0.0697)	(0.0681)	(0.0681)	(0.0700)	(0.0683)	(0.0631)	(0.0715)	(0.0682)
Guizhou	-0.0876	-0.1609***	-0.5416***	-0.0757	-0.1760***	-0.5418***	-0.1162*	-0.2094***	-0.5418***
	(0.0610)	(0.0516)	(0.0646)	(0.0634)	(0.0517)	(0.0644)	(0.0598)	(0.0529)	(0.0644)
Rural	-0.2272***	-0.1663***	-0.2195***	-0.2178***	-0.1723***	-0.2199***	-0.2495***	-0.1855***	-0.2197***
	(0.0309)	(0.0238)	(0.0277)	(0.0337)	(0.0238)	(0.0278)	(0.0318)	(0.0236)	(0.0280)
Primary school	0.0762*	0.0063	0.0416	0.0729	0.0104	0.0424	0.0840**	0.0194	0.0422
	(0.0441)	(0.0390)	(0.0453)	(0.0451)	(0.0384)	(0.0456)	(0.0426)	(0.0379)	(0.0455)
Secondary school	0.1401***	0.1399***	0.0561	0.1316***	0.1508***	0.0573	0.1605***	0.1750***	0.0569
	(0.0440)	(0.0357)	(0.0417)	(0.0460)	(0.0357)	(0.0427)	(0.0436)	(0.0358)	(0.0426)
High school	0.1863***	0.2177***	0.0619	0.1709***	0.2350***	0.0641	0.2230***	0.2731***	0.0633
	(0.0515)	(0.0420)	(0.0500)	(0.0559)	(0.0428)	(0.0525)	(0.0523)	(0.0431)	(0.0528)
Vocational training	0.2125***	0.3429***	0.1450**	0.1853**	0.3740***	0.1477**	0.2773***	0.4427***	0.1468**
	(0.0625)	(0.0534)	(0.0608)	(0.0728)	(0.0562)	(0.0649)	(0.0699)	(0.0581)	(0.0645)
University & higher	0.0783	0.1996***	0.0768	0.0425	0.2411***	0.0804	0.1637*	0.3327***	0.0792
	(0.0773)	(0.0640)	(0.0691)	(0.0922)	(0.0682)	(0.0757)	(0.0887)	(0.0712)	(0.0758)
Age	0.0047	-0.0128*	-0.0074	0.0052	-0.0119*	-0.0073	0.0035	-0.0099	-0.0074
	(0.0083)	(0.0071)	(0.0076)	(0.0085)	(0.0070)	(0.0076)	(0.0079)	(0.0069)	(0.0076)
Age squared (divided by 100)	-0.0074	0.0173**	0.0066	-0.0082	0.0162*	0.0066	-0.0054	0.0140*	0.0066
	(0.0101)	(0.0086)	(0.0092)	(0.0104)	(0.0085)	(0.0091)	(0.0096)	(0.0084)	(0.0092)

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Female	0.1158***	0.1770***	0.1521***	0.1133***	0.1797***	0.1523***	0.1216***	0.1856***	0.1523***
	(0.0242)	(0.0214)	(0.0232)	(0.0250)	(0.0211)	(0.0232)	(0.0234)	(0.0206)	(0.0232)
Food consumption (kg)	0.4354***	0.6048***	0.4915***	0.4310***	0.6184***	0.4925***	0.4461***	0.6483***	0.4922***
	(0.0350)	(0.0307)	(0.0337)	(0.0363)	(0.0313)	(0.0342)	(0.0342)	(0.0316)	(0.0339)
Household size (adult equivalent)	0.0381***	0.0263**	0.0353**	0.0428***	0.0182	0.0346**	0.0268*	0.0005	0.0349**
	(0.0147)	(0.0127)	(0.0146)	(0.0162)	(0.0136)	(0.0156)	(0.0154)	(0.0140)	(0.0154)
Rice price	0.0104	0.2403***	0.0165	0.0109	0.2591***	0.0157	0.0090	0.3007***	0.0160
	(0.0381)	(0.0696)	(0.0538)	(0.0391)	(0.0691)	(0.0543)	(0.0361)	(0.0680)	(0.0543)
Pork price	-0.0098	-0.0318	0.1338***	-0.0084	-0.0303	0.1343***	-0.0130	-0.0268	0.1341***
	(0.0309)	(0.0316)	(0.0477)	(0.0315)	(0.0312)	(0.0479)	(0.0298)	(0.0305)	(0.0478)
Fish price	0.0229	-0.3099***	-0.0581	0.0312	-0.3086***	-0.0591	0.0031	-0.3057***	-0.0588
	(0.0482)	(0.0561)	(0.0520)	(0.0507)	(0.0551)	(0.0525)	(0.0471)	(0.0536)	(0.0526)
Cabbage price	0.0038	-0.0083	0.0921***	0.0006	-0.0076	0.0925***	0.0114	-0.0063	0.0924***
	(0.0167)	(0.0186)	(0.0229)	(0.0175)	(0.0182)	(0.0230)	(0.0167)	(0.0178)	(0.0231)
Tofu price	-0.1219***	-0.0316	-0.1429***	-0.1210***	-0.0308	-0.1429***	-0.1242***	-0.0293	-0.1429***
	(0.0303)	(0.0305)	(0.0339)	(0.0308)	(0.0300)	(0.0339)	(0.0289)	(0.0294)	(0.0339)
Apple price	-0.0243	-0.0806	0.1640***	-0.0306	-0.0608	0.1638***	-0.0092	-0.0172	0.1639***
	(0.0381)	(0.0510)	(0.0413)	(0.0397)	(0.0521)	(0.0414)	(0.0372)	(0.0527)	(0.0414)
Soy oil price	0.1818***	0.1313***	0.2759***	0.1759***	0.1315***	0.2760***	0.1959***	0.1319***	0.2760***
	(0.0435)	(0.0277)	(0.0461)	(0.0450)	(0.0274)	(0.0460)	(0.0420)	(0.0271)	(0.0461)
Constant	-2.1833***	1.1656***	-0.2502	-2.5181***	1.5207***	-0.2151	-1.3837**	2.3048***	-0.2271
	(0.4582)	(0.3506)	(0.4656)	(0.6461)	(0.4069)	(0.5445)	(0.6149)	(0.4592)	(0.5495)
N	5182	4970	5010	5182	4970	5010	5182	4970	5010
R-sq	0.012	0.243	0.055	.	0.267	0.059	0.098	0.301	0.057
Adj. R-sq	0.007	0.239	0.050	.	0.263	0.054	0.094	0.297	0.052
RMSE	0.8197	0.7103	0.7721	0.8365	0.6989	0.7706	0.7833	0.6828	0.7711

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

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