China Economic Review 59 (2020) 101135

Contents lists available at ScienceDirect

China Economic Review

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

Projecting meat and cereals demand for China based on a meta-analysis of income elasticities☆

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ARTICLE INFO

JEL codes:
D12
Q11

Keywords:
Projections
Food demand
Income elasticity
China
Meta-analysis

ABSTRACT

There are many projections for China's food demand, and the projection results differ significantly from each other. Different values for income elasticities could be a major reason. This study projects meat and cereals demand for China based on a meta-analysis of the income elasticity estimates using a collection of 143 and 240 income elasticity estimates for cereals and meat products, respectively, from 36 primary studies. We find that income elasticities for most cereals (general cereals, rice, and coarse grains) and all meat products (general meat, pork, poultry, beef & mutton) tend to decline as per capita income increases, except for wheat, which increases. Taking this into account, differences between consumption projections based on time-varying income elasticities and values based on constant elasticities are substantial in quantities and increase over time.

1. Introduction

In conjunction with rapid economic growth for more than three decades, China is experiencing significant structural changes in food consumption (Yu & Abler, 2009; Zhou, Yu, & Herzfeld, 2015). Understanding these changes and what they portend for future food consumption has important implications for food policy, particularly for a country with the sheer population size and GDP of China. And as an emerging economy, China's structural changes in food consumption may also carry policy lessons for other developing countries.

China has been the subject of extensive empirical studies on food demand during the past two decades using a wide range of models and data sources (e.g. Abler, 2010; Chern & Wang, 1994; Fan, Cramer, & Wailes, 1994; Fan, Wailes, & Cramer, 1995; Gao, Wailes, & Cramer, 1996; Gould & Villarreal, 2006; Huang & Rozelle, 1998; Jiang & Davis, 2007; Lewis & Andrews, 1989; Liu, 2003; Wu, Li, & Samuel, 1995; Yen, Fang, & Su, 2004; Yu, 2018; Zheng & Henneberry, 2009). However, the estimated demand elasticities in the literature are quite varied, and some even controversial (Abler, 2010). For instance, the income elasticity for wheat reaches as

☆ An earlier version of this paper was presented in 2013 Annual Meeting of Chinese Economists Society in Chengdu, China. We are very grateful to the participants for their fruitful comments. In addition, we also thank Dr. Junfei Bai at China Agricultural University, Dr. Jim Hansen at USDA/ERS, Prof. Matin Qaim at the University of Goettingen, and Dr. Wei Chen at the Shanghai University of Finance and Economics for their constructive comments on earlier versions of this paper. Funding Support from the German Research Foundation (DFG, RTG-1666) and "A Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD)" is acknowledged.

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https://doi.org/10.1016/j.chieco.2017.12.002
Received 1 December 2015; Received in revised form 1 December 2017; Accepted 1 December 2017
Available online 05 December 2017
1043-951X/

high as 1.1 in a study by Han, Cramer, and Wahl (1997), much greater than the − 0.37 estimated by Carter and Zhong (1999).

The elasticities obtained from the empirical demand analyses are often used for projection of food demand, which could help make better food policies. Though there are many projections for China's food demand, and the projection results often differ significantly from each other. Fan and Agcaoili-Sombilla (1997) and Yu, Hertel, Preckel, and Eales (2003) provide good reviews of these projections. Given the tight domestic food supply situation in China, and the sheer size of the population, incorrect projections could lead to inappropriate agricultural and trade policies, which could impact world food markets.

Fan and Agcaoili-Sombilla (1997) attribute projection differences for China to three factors: macroeconomic assumptions, model structure, and model parameters (demand and supply elasticities). Demand elasticities are central to projections of future food consumption, so their accuracy and credibility are important. Income elasticities are particularly important for gauging the growth of food demand in the case of China because of China's rapid rate of per capita income growth. A synthesis of existing research is needed to determine a reasonable set of estimates for these elasticities in light of the heterogeneity in estimates in the literature, and what this set of estimates implies for future food consumption in China.

This paper conducts a meta-analysis of income elasticity estimates for meat and cereal products in China, which systematically studies the heterogeneities in the elasticities. A meta-analysis is a quantitative analysis of a body of similarly related primary studies to summarize the results or evaluate the reliability of the findings (Card & Krueger, 1995). We use a meta-regression approach in which study results are regressed on key characteristics of each study (Stanley & Doucouliagos, 2012). Similar to meta-analyses of the income elasticity of demand for cigarettes (Gallet & List, 2003), alcohol (Gallet, 2007), meat (Gallet, 2010a), calories (Ogundari & Abdulai, 2013) and Chinese total factor productivity (TFP) (Tian & Yu, 2012), we use the estimated income elasticities from the primary studies as the dependent variable in the meta regressions.

Many types of food products are analyzed in the food demand literature for China. We focus in this paper on two groups of products, cereals and meat. These are the two most important groups of food products in Chinese diets, as they are the main calorie sources (Tian & Yu, 2013; Yu, Gao, & Zeng, 2014). In particular, meat consumption is linked to sustainable development (Hasiner & Yu, 2016), because the continuously increasing meat consumption in China may stress the environment and international food security, and hence has drawn a lot of attention both in the policy and the academic arenas. Statistics from the National Bureau of Statistics of China (NBSC) in the *China Yearbook of Household Survey* indicate that the shares of cereals and meat in total food expenditure were 8% and 20%, respectively, for urban China in 2011 and 14% and 21%, respectively, for rural China in 2011. Cereals and meat are also the two groups of food products in China for which there are the largest number of estimates of income elasticities.

As part of the meta-analysis we examine two questions pertinent to future food consumption in a country such as China that is growing economically and becoming more urbanized. First, is there a relationship between income elasticities and per capita income levels, and if there is, how do elasticities change as income grows? Engel's law indicates that the share of food expenditure in total household consumption will decline in company with income growth, and it implies that the income elasticity will become less sensitive (Yu, 2018). However, most of the current projections have not taken into this factor, and often use constant elasticities. The projections will cause substantial bias, mainly bias up particularly in the long run. Second, after controlling for per capita income, is there a systematic difference in income elasticities between rural and urban households? One can expect that the income elasticities in rural areas will be higher than in urban areas as the income in rural areas is lower, and the dietary is more dominated by tradition fiber food. The projection for food demand in China should separately shed light on rural and urban areas. The two questions are empirically supported by our meta-analysis. Accordingly, we project the demand for rural and urban separately as well.

The rest of the paper is structured as follows: Section 2 introduces the data on income elasticities for cereals and meat demand in China; Section 3 describes the meta-regression models estimated in this paper; Section 4 outlines the variables hypothesized to explain heterogeneities in income elasticity estimates; Section 5 presents the meta-regression results; Section 6 derives projections of income elasticities based on the meta-regression results and what these projections mean for future Chinese food demand; and Section 7 contains conclusions and policy implications.

2. Data

A meta-analysis first needs to compile a dataset which consists of the meta variables of primary interest (income elasticity in this paper) and the characteristics that may explain heterogeneities in the meta variable. We conducted online keyword searches using Google, Google Scholar, AgEcon Search, EconLit, a USDA demand elasticity database (USDA/Economic Research Service, 2012), Web of Science, and China National Knowledge Infrastructure (CNKI). We also searched backward and forward in time for each study located—references cited by a study, and subsequent papers referencing the study in question. We attempted to collect as many primary studies as possible, since Walker, Hernandez, and Kattan (2008) pointed out that meta-analyses may suffer from selection bias due to the search criteria for primary studies. Given the focus of this paper, the primary criteria for selecting studies are those that include cereals or meat products or both. In the literature on China, "cereals" are generally defined to be all cereals, wheat, rice, and/or coarse grains, while "meat" is generally defined to be all meat, pork, beef & mutton, and/or poultry. These product categorizations are in line with those in the rural and urban household surveys conducted annually by NBSC.

There are different definitions of "income" elasticity in the literature. We can plausibly assume that household income is equal to total household expenditure in the long run, so that the correct definition of an "income" elasticity should be the demand elasticity with respect to total income (income elasticity) or total household expenditure (total expenditure elasticity). In the short run, of course, income and expenditure can differ because of savings and borrowing. For the sake of simplicity, we hereafter do not differentiate between income elasticity and total expenditure elasticity, and call them both "income elasticity."

Many of the studies for China model food product demands as a function of total food expenditure or expenditure on a particular

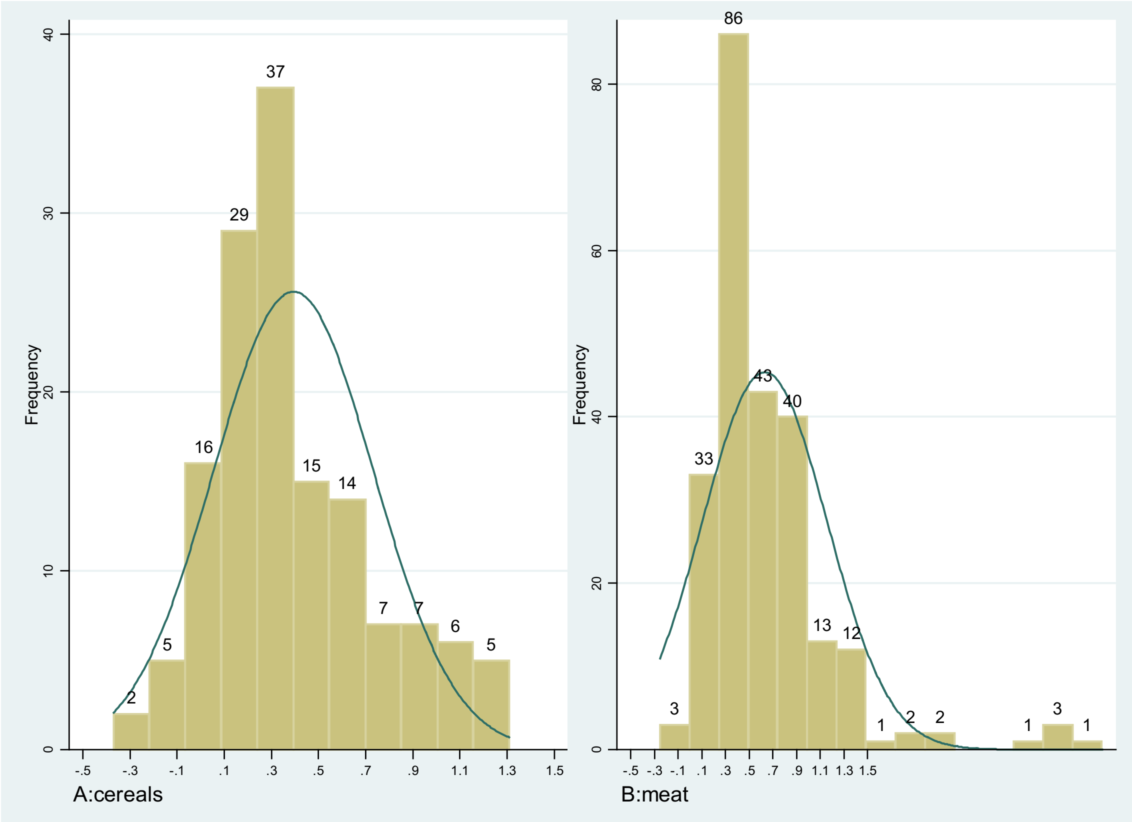

Fig. 1. Distribution of estimated income elasticities in the primary studies.

food group (e.g. meat) rather than as a function of total household income or total household expenditure. As a result, the elasticity estimates from those studies are with respect to total food expenditure or expenditure on that food group rather than with respect to total household income or expenditure. These elasticities are referred to in the literature as conditional elasticities, while elasticities with respect to total household income or total expenditure are referred to as unconditional elasticities. Conditional elasticity estimates tend to be larger—often much larger—than unconditional elasticity estimates because the elasticity of total food expenditure or food group expenditure with respect to total income is generally less than one (Jiang & Davis, 2007). Conditional elasticity estimates also raise concerns about endogeneity bias because many studies treat total food expenditure or food group expenditure as exogenous, whereas in fact they are household decision variables (Thompson, 2004). Conditional elasticity estimates are hence ruled out in this research.

With these criteria, we collected 36 primary studies shedding light on cereals and meat demand in China, of which 25 are in the English language and 11 in the Chinese language. These studies yielded 143 income elasticity estimates for cereals and 240 estimates for meat products. The primary studies are listed in the appendix. Fig. 1 shows the distribution of income elasticity estimates across these food categories in our dataset. The mean value for cereals is 0.39 with a standard deviation of 0.34. For the meat group, the mean is 0.63 with a standard deviation of 0.53. These statistics indicate that there are large variations in income elasticity estimates for cereals and meat that deserve further investigation. They provide evidence that we should pay attention to the factors behind these variations when using them for food consumption projections.

3. Meta-regression models

Similar to other meta-analyses (Alston, Marra, Pardey, & Wyatt, 2000; Gallet, 2007, 2010a, 2010b; Tian & Yu, 2012), we first specify a linear meta-regression model. The estimated income elasticity E_i collected from the primary studies serves as the dependent variable:

$$E_i = \alpha + X_i\beta + u_i \tag{1}$$

X_i is a vector of explanatory variables discussed below, β is a vector of coefficients, α is an intercept, and u_i is an error term which is assumed to follow a normal distribution. The meta-regression models pool elasticity estimates for different products in order to increase degrees of freedom. Product dummy variables are included in the models, as described below.

Heteroskedasticity is a common issue in meta-regression modeling (Nelson & Kennedy, 2009; Ogundari & Abdulai, 2013; Stanley

& Doucouliagos, 2012; Tian & Yu, 2012). Due to different primary sample sizes and different estimation procedures, demand elasticity estimates generally have heterogeneous variances. Estimates with smaller variances are more reliable and should be given greater weight in the meta-regression. However, variances are usually unavailable as the primary studies generally do not report variances for their income elasticity estimates. Following other meta-analyses such as Nelson and Kennedy (2009), one common method for dealing with this problem is to proxy the variances using the sample sizes of the primary studies, because the variance is often negatively correlated with the sample size. Therefore, in addition to ordinary least squares (OLS), this paper also employs weighted least squares (WLS) using the primary study sample size as the weight.

The meta-analysis literature also indicates that the meta-regression model might not be linear (Walker et al., 2008). A Box−Cox model often serves to address this issue:

$$(E_i^{\theta} - 1)/\theta = \alpha + X_i\beta + u_i \tag{1}$$

θ is a parameter which indicates the specification of the functional form, including the special cases of linear ($\theta = 1$) and logarithmic ($\theta = 0$). However, the Box-Cox transformation requires positive values of the transformation variable. There are 11 negative demand elasticity estimates for cereals and 3 negative estimates for meat in our primary observations, and so these observations must be omitted from the Box-Cox models. This means that the Box-Cox estimates are conditional on the assumption that cereals and meat products are normal goods. Five estimates in the meat sample are larger than three standard deviations from the mean, and so they are also excluded from the Box-Cox models as outliers. The remaining restricted samples for the Box-Cox analyses consist of 132 observations for cereals and 232 observations for meat. For comparison purposes, we estimate the OLS and WLS models in Eq. (1) using both the full samples and the restricted samples.

4. Explanatory variables

Alston et al. (2000) suggest that variation in results among primary studies can be attributed to several aspects including characteristics of the research, analysis, evaluation process, and random measurement errors. Tian and Yu (2012) classify the factors accounting for heterogeneities among primary studies into two categories: contextual factors and methodological factors. A similar categorization is adopted in this study. The contextual factors explain real differences in the results between primary studies, such as differences in food categories, locations studied, and time periods studied; while methodological factors are extrinsic to the population being studied, such as study designs and budgeting processes, demand models, estimation procedures, and the peer-review process (Nelson & Kennedy, 2009; Smith & Pattanayak, 2002).

Table 1 provides a statistical description of those factors that are included in the meta-analyses. Table 2 presents definitions of the variables that are included in the econometric models.

4.1. Product differences

It is well known that income elasticities vary across food groups. For instance, necessities such as cereals usually have small income elasticities, while meat products often have higher income elasticities. Table 1 provides evidence of this: the average income elasticity for cereals is 0.39, quite smaller than the 0.63 average for the meat group. It is interesting that the mean income elasticities for group aggregates are smaller than those for specific products in that group. For instance, the mean elasticity for general cereals is 0.34, while the elasticities for wheat, rice and coarse grains respectively are 0.42, 0.49 and 0.48. The mean elasticity for general meat is 0.53, while the values for pork, beef & mutton, and poultry respectively are 0.67, 0.54 and 0.72. In theory the income elasticity for a group should be a weighted average of the income elasticities for the products in that group. In this regard we should bear in mind that the statistics in Table 1 come from different sets of studies covering different time periods and locations. We control for product differences in the meta-regression analyses using product dummy variables.

4.2. Per capita income

The literature has different definitions and sources of income (or expenditure). As aforementioned, we basically assume total expenditure is equal to income. In our analysis, first, if the paper reports the values of per capita income (total expenditure), we just use it. Second, if the paper does not report the income or expenditure, we will use the values of that region (province) in the study year from the Yearbook of Household Surveys from the National Bureau of Statistics of China to represent it. We believe the difference will not be such huge.

Cross-country demand studies have found that income elasticities of demand for food items generally decline as per capita income increases (Muhammad et al., 2011; Yu et al., 2003; Yu, 2018). Among various food product categories, Muhammad et al. (2011) found that income elasticities for cereals decline the most as per capita income increases, while declines for meat products are smaller. These findings are consistent with evidence for China from Jensen and Miller (2010) on the shares of total calories from cereals and meat at different income levels. We test whether these findings hold in our dataset by including the log of per capita income as an explanatory variable in the meta-regressions. To allow for different effects of per capita income depending on the product, we include interaction terms between the log of per capita income and the product dummy variables.

Table 1
Summary statistics for income elasticities by study characteristics.

		Cereals			Meat		
		Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
	Total	143	0.394	0.340	240	0.632	0.525
	Log income	143	7.908	1.059	240	7.892	1.054
Product	General cereal	78	0.340	0.330			
	Wheat	29	0.417	0.328			
	Rice	30	0.493	0.368			
	Coarse grain	6	0.479	0.322			
	General meat				46	0.525	0.346
	Pork				62	0.674	0.397
	Beef & mutton				50	0.535	0.439
	Poultry				82	0.718	0.701
Region	Urban	87	0.274	0.225	141	0.556	0.595
	Rural	56	0.580	0.402	99	0.739	0.383
	National	41	0.528	0.486	75	0.778	0.783
	Regional	102	0.340	0.243	165	0.565	0.333
Data	D_micro	85	0.482	0.381	135	0.608	0.352
	D_macro	58	0.264	0.213	105	0.662	0.687
	D_cross-section	117	0.435	0.335	195	0.541	0.329
	D_pooled	15	0.143	0.285	28	1.220	1.062
	D_panel	11	0.297	0.325	17	0.701	0.443
Publication	Pub_wp	25	0.703	0.406	27	0.526	0.305
	Pub_journal	98	0.318	0.298	161	0.652	0.602
	Pub_report	20	0.378	0.219	52	0.625	0.320
	Pub_english	101	0.431	0.387	168	0.711	0.582
	Pub_chinese	42	0.305	0.153	72	0.447	0.285
Specification	Multistage0	47	0.247	0.270	99	0.703	0.607
	Multistage1	96	0.466	0.349	141	0.582	0.455
	Inc_elast	90	0.203	0.175	156	0.533	0.596
	Exp_elast	53	0.717	0.307	84	0.814	0.282
	Pragmatic model	18	0.049	0.191	58	0.674	0.781
	Demand system	125	0.444	0.328	182	0.618	0.414
	Model_rank2	96	0.470	0.341	139	0.606	0.414
	Model_rank3	29	0.355	0.269	43	0.659	0.415
	Demographic0	35	0.239	0.318	58	0.902	0.838
	Demographic1	108	0.444	0.334	182	0.545	0.335
Estimation	Ols_est	14	0.129	0.142	32	0.882	0.941
	Sls_est	7	0.077	0.247	15	0.534	0.560
	Sur_est	86	0.507	0.330	133	0.613	0.427
	Ml_est	22	0.259	0.240	25	0.511	0.294
	Gmm_est	3	0.199	0.163	6	0.267	0.134
	Other_est	11	0.374	0.447	29	0.670	0.398

The mean income elasticity is calculated from all estimations in each respective category.

4.3. Rural-urban differences

Consumption patterns differ between rural and urban households. Statistics from the NBSC rural and urban household surveys indicate that per capita consumption of cereals is significantly greater in rural areas than in urban areas, while the opposite is true for meat. Table 1 provides summary statistics for income elasticities for urban and rural households. The mean income elasticity for cereals is 0.27 for urban households, much smaller than the mean of 0.58 for rural households. Similarly, the mean income elasticities for meat are 0.56 and 0.74 for urban and rural households, respectively. A key question is whether any rural-urban differences in income elasticities remain after controlling for per capita income. The answer to this question might be yes because urban households generally have access to a wider variety of food products than rural households, including processed and pre-prepared foods, have more restaurant options for dining out, and tend to have lower levels of physical activity. We include a dummy variable for urban data to test for rural-urban differences.

4.4. Other data differences

We use dummy variables to control for four other types of data differences in addition to per capita income and rural-urban differences: (1) how “income” is measured (total household expenditure or total household income); (2) whether the data are for China as a whole or specific regions of China; (3) whether the data are micro-level (household) or aggregate data; and (4) whether the data are cross-sectional, pooled, or panel.

Even though our sample is limited to studies where income is measured by total household expenditure or total household

Table 2
Variable definitions.

Variable	Definition
pub_journal	Dummy for journal
pub_wp	Dummy for unpublished papers
pub_report	Dummy for reports, books, and dissertations
pub_english	Dummy for primary studies written in English language
h_urban	Dummy for urban households
h_nation	Dummy for regional-level study: China = 1, local region = 0
d_micro	Dummy for micro data: micro = 1, aggregation = 0
d_cross-section	Dummy for cross-section data
d_pooled	Dummy for pooled data
d_panel	Dummy for panel data
model_type	Dummy for demand system: demand system = 1, pragmatic model = 0
model_rank2	Dummy for rank 2 model
budget_stage	Dummy for multi stage demand system: single-stage = 1, multi-stage = 0
elasticity_inc	Dummy for demand elasticity with respect to income (= 1) versus total expenditure (= 0)
demographic	Dummy for demand model with demographic variables
ols_est	Dummy for OLS
sls_est	Dummy for 2SLS
sur_est	Dummy for SUR
ml_est	Dummy for ML
gmm_est	Dummy for GMM
other_est	Dummy for other estimation methods
lnincome	Log of per capita annual disposable (net) income
inter_*	Interaction effect between a commodity dummy (represented by *) and log of per capita income

income, there appear to be differences between these two types of studies. In our sample, 90 estimates for cereals are total income elasticities and the rest (53 estimates) are total expenditure elasticities. Meanwhile, 156 observations for meat are total income elasticities and the rest (84) are expenditure elasticities. The mean income elasticities are lower than the expenditure elasticities: mean total income and expenditure elasticities are 0.203 and 0.717 for cereals, respectively, and 0.533 and 0.814 for meat products, respectively. We control for this difference analyses using a dummy variable.

China is a large country with significant regional differences, including heterogeneity in tastes (Yu et al., 2014). For example, people tend to consume more rice in southern provinces, while people in the north prefer wheat (Fan et al., 1994). In the primary studies, some estimates focus on the national level (e.g. Fan et al., 1995; Lewis & Andrews, 1989; Wu et al., 1995), while others use regional datasets (e.g. Gao et al., 1996; Jiang & Davis, 2007; Liu, 2003; Zheng & Henneberry, 2009). Table 1 presents the regional differences in income elasticities for each food group. Generally, the mean values reported in Table 1 for income elasticities from nationwide studies are higher than those from regional-level studies. Most of the regional studies were conducted in more developed areas such as Guangdong, Jiangsu, and Shandong provinces.

Systematic differences in elasticities have sometimes been found depending on whether the data are micro household survey data or aggregate data; and whether the data are cross-sectional, pooled, or panel (Gallet, 2010b; Ogundari & Abdulai, 2013). Micro household survey data are often considered superior to aggregate data because the former are more compatible with demand theory and may include demographic characteristics that make it possible to test for heterogeneity in preferences across households (Zheng & Henneberry, 2009). Panel data are often considered superior to cross-sectional data in controlling for unobservable heterogeneities in consumer choice (Deaton, 1985; Yu & Abler, 2009).

4.5. Modeling and estimation differences

We use dummy variables to control for four types of modeling and estimation differences: (1) whether the budgeting process was assumed to be single-stage or multi-stage; (2) the type of demand system (or lack of a demand system) in the primary study; (3) whether or not the study included controls for demographic characteristics; and (4) the type of estimation procedure in the primary study.

Multi-stage budgeting occurs when a consumer allocates total expenditure in sequential stages, such as a two-stage budgeting model in which the consumer decides on total food expenditure at the first stage and then the quantities of individual food items at the second stage. Multi-stage budgeting requires that the consumer's utility function be weakly separable among groups of goods (Deaton, 1986), a restriction that may impact estimated income elasticities. Table 1 indicates that most primary studies adopt multi-stage budgeting, and their mean income elasticity is 0.466 for cereals, which is higher than the mean for single-stage studies (0.247). In contrast, the mean elasticities for meat products are 0.582 and 0.703 for multi-stage and single stage studies, respectively.

While older studies typically used pragmatic (or ad hoc) demand models that had little connection with microeconomic theory, such as a log-linear model, the majority of studies for China during the past two decades have used demand systems based on modern consumer theory. Among demand systems, Lewbel (1991) classifies them according to their rank, i.e. the maximum dimension of the function space spanned by their Engel curves. All modern demand systems have a rank of two or greater, with Engel curves having the ability to take on increasingly complex shapes as the rank increases. For example, the almost ideal demand system (AIDS) is of rank two while the quadratic almost ideal demand system (QUAIDS) is of rank three. We include dummy variables for whether the primary study used a demand system, and if so whether it was of rank two. Meyer, Yu, & Abler (2011) used Monte-Carlo simulations to show the differences between these demand models.

Demographic variables such as educational levels and the age and gender composition of the household are obviously important determinants of consumption patterns. Whether estimated income elasticities are affected by the inclusion or exclusion of demographic variables is not as clear (Jiang & Davis, 2007). There are many possible demographic variables and different studies model demographic effects in different ways. For the sake of parsimony, we use a single dummy variable for whether the demand model in a primary study took account of demographic effects. Table 1 indicates that most of the studies (108 elasticities for cereals and 182 elasticities for meat) include demographic variables.

Many different estimation procedures have been used in estimating demand systems, which might be associated with heterogeneities in the estimated elasticities. Seemingly unrelated regression (SUR) is the most popular econometric method in the current food demand literature, but there are many other estimation methods, including ordinary least squares (OLS), two-stage least squares (2SLS), maximum likelihood (ML), generalized method of moments (GMM), and a few other less common methods collectively labeled here as “other estimation methods.” Dummy variables are included to control for the various estimation methods.

4.6. Publication bias

Publication bias can occur because reviewers and editors may be more likely to accept papers for publication that have results that are statistically significant, large in magnitude, and/or consistent with conventional views; researchers in turn may selectively report results based on their expectations of what reviewers and editors are looking for (Stanley & Doucouliagos, 2012; Tian & Yu, 2012; Walker et al., 2008). In order to control for potential publication bias, we include dummy variables to distinguish peer-reviewed published studies from unpublished working papers, and from results in book chapters and reports. Similarly, we use a dummy variable to control for potential publication bias associated with the language (English or Chinese) of the primary study.

Table 1 indicates that 25 income elasticity estimates for cereals are from unpublished working papers, 20 are from book chapters or reports, while the rest (98) come from peer-reviewed journals. A similar pattern is observed for meat studies. Regarding language, 101 of the 143 observations for cereals, and 168 of the 240 observations for meat products, were collected from English language studies, and the rest are from Chinese language studies.

5. Meta-regression results

The meta-regression results for cereals and meat products are reported in Tables 3 and 4, respectively. The results across the different econometric specifications (OLS, WLS, and Box-Cox; full and restricted samples) are generally similar in the signs and significance levels of the estimated coefficients, implying that our results are robust. The adjusted R^2 values for the OLS and WLS models using the restricted sample are larger than their corresponding values for the full sample, indicating that dropping the unusual income elasticity estimates improves the overall fit of the model. The WLS models have higher adjusted R^2 values than the OLS models, which is consistent with the hypothesis that heteroskedasticity exists in these linear meta-regressions.

For cereals, the estimated θ for the Box-Cox transformation parameter is 0.50 with a standard error of 0.29. Both the null hypothesis of $\theta = 0$ (log-linear specification) and the null hypothesis of $\theta = 1$ (linear) are rejected at the 10% level. For meat products, the null hypothesis of $\theta = 1$ is rejected but the null hypothesis of $\theta = 0$ cannot be rejected, suggesting that the log-linear form may be a suitable model specification.

Between the Box-Cox and WLS models, comparing adjusted R^2 values does not provide statistically valid evidence on which model better fits the data, as the models are non-nested. Non-nested models can be tested by a general likelihood ratio test developed by Vuong (1989). Table 5 presents the results of Vuong's test, which rejects the linear model in favor of the Box-Cox model for both cereals and meat. Therefore, the following discussion is based on the Box-Cox results, bearing in mind that the OLS and WLS results are similar.

5.1. Per capita income and product differences

For cereals, the log of per capita income, the wheat dummy, and the interaction term between the log of per capita income and the wheat dummy are statistically significant. The results indicate that income elasticities for cereals in general, rice, and coarse grains decline as per capita income increases. The marginal effect for cereals in general is -0.142, so that a doubling of per capita income would lead to a decline of $\ln(2) \times 0.142 \approx 0.10$ in the income elasticity. For wheat, the total marginal effect including the interaction term is $-0.142 + 0.183 = 0.041$, so that the income elasticity for wheat does not decline with per capita income growth. Richer households in China often consume Western-style foods, in which the predominant source of carbohydrates is high-protein wheat, given their convenience (Bai, McCluskey, Wang, & Min, 2014).

For meat products, the pork dummy, poultry dummy, and the interaction term between the log of per capita income and the pork dummy are statistically significant. The marginal effect for the log of per capita income is -0.055, a relatively small number and not statistically significant. The results imply that income elasticities for meat products as a whole, beef & mutton, and poultry do not change significantly with income growth. For pork, the total marginal effect including the interaction term is $-0.055–0.166 = -0.221$, so that a doubling of per capita income would lead to a decline of $\ln(2) \times 0.221 \approx 0.15$ in the income elasticity for pork. Section 6 below contains projections of income elasticities at different income levels.

Table 3
Meta-regression results for cereals.

Explanatory Variable	Full Sample		Restricted Sample		
	OLS	WLS	OLS	WLS	Box-Cox
pub_wp	0.269***	0.355***	0.402***	0.460***	0.511**
	(0.08)	(0.08)	(0.07)	(0.08)	[0.385]
pub_journal	0.248***	0.310***	0.298***	0.331***	0.260
	(0.07)	(0.06)	(0.06)	(0.06)	[0.174]
pub_english	− 0.001	− 0.096	− 0.067	− 0.187	− 0.266*
	(0.07)	(0.16)	(0.06)	(0.16)	[− 0.186]
h_urban	− 0.032	− 0.138	− 0.024	− 0.175*	− 0.097
	(0.06)	(0.09)	(0.05)	(0.09)	[− 0.065]
h_nation	0.213***	0.212***	0.169***	0.168**	0.243**
	(0.05)	(0.07)	(0.04)	(0.07)	[0.173]
d_micro	0.028	0.076	0.050	0.123	0.107
	(0.06)	(0.15)	(0.05)	(0.14)	[0.071]
d_cross-section	0.143	0.211**	0.215***	0.235***	0.206*
	(0.09)	(0.09)	(0.08)	(0.08)	[0.129]
d_pooled	− 0.157	− 0.210	0.062	0.006	− 0.104
	(0.10)	(0.20)	(0.10)	(0.21)	[− 0.067]
model_type	− 0.210*	− 0.254	− 0.313***	− 0.443	− 0.481*
	(0.12)	(0.42)	(0.10)	(0.50)	[− 0.383]
model_rank2	0.061	0.026	0.072*	0.023	0.037
	(0.05)	(0.03)	(0.04)	(0.03)	[0.025]
budget_stage	0.038	0.021	0.048	0.023	0.015
	(0.05)	(0.07)	(0.05)	(0.07)	[0.01]
elasticity_inc	− 0.515***	− 0.451***	− 0.523***	− 0.413***	− 0.611***
	(0.06)	(0.08)	(0.05)	(0.07)	[− 0.409]
Demographic	0.139**	0.030	0.128**	0.032	0.041
	(0.07)	(0.07)	(0.06)	(0.06)	[0.027]
sls_est	− 0.279**	− 0.373	− 0.296**	− 0.400	− 0.499*
	(0.13)	(0.30)	(0.12)	(0.35)	[− 0.275]
sur_est	− 0.008	0.061	0.085	0.189	0.264
	(0.11)	(0.41)	(0.10)	(0.46)	[0.167]
ml_est	0.072	0.145	0.194*	0.285	0.395
	(0.12)	(0.41)	(0.11)	(0.46)	[0.294]
gmm_est	0.386**	0.525	0.520***	0.675	0.753*
	(0.16)	(0.46)	(0.14)	(0.50)	[0.651]
other_est	− 0.228**	− 0.178	− 0.096	− 0.062	0.036
	(0.10)	(0.41)	(0.10)	(0.46)	[0.024]
lnincome	− 0.106***	− 0.106***	− 0.121***	− 0.119***	− 0.210**
	(0.02)	(0.03)	(0.02)	(0.03)	[− 0.142]
Wheat	− 0.803***	− 1.088***	− 1.000***	− 1.250***	− 2.142**
	(0.28)	(0.28)	(0.25)	(0.27)	[− 0.832]
Rice	− 0.302	− 0.261	− 0.461*	− 0.387	− 1.062
	(0.28)	(0.27)	(0.24)	(0.26)	[− 0.574]
Coarse grain	− 1.098**	− 0.432	− 1.379***	− 0.621	− 0.974
	(0.46)	(0.45)	(0.39)	(0.43)	[− 0.439]
inter_wheat	0.118***	0.149***	0.134***	0.162***	0.272**
	(0.04)	(0.03)	(0.03)	(0.03)	[0.183]
inter_rice	0.058*	0.049	0.069**	0.057*	0.142
	(0.03)	(0.03)	(0.03)	(0.03)	[0.095]
inter_coarse grain	0.134**	0.053	0.159***	0.070	0.105
	(0.06)	(0.06)	(0.05)	(0.05)	[0.071]
Constant	1.157***	1.228***	1.238***	1.405***	1.093
	(0.23)	(0.31)	(0.21)	(0.34)	(0.73)
Theta (Θ)					0.496*
					(0.29)
Adjusted R^2	0.812	0.865	0.859	0.879	1.000
Sample Size	143	143	132	132	132

Standard errors are provided in parentheses, while marginal effects for the Box-Cox model (evaluated at sample means) are provided in brackets.
The dependent variable in each regression is the income elasticity.

*** 1% level of significance.
** 5% level of significance.
* 10% level of significance.

Table 4
Meta-regression results for meat products.

Explanatory Variable	Full Sample		Restricted Sample		
	OLS	WLS	OLS	WLS	Box-Cox
pub_wp	0.159	0.042	0.230**	0.063	0.290**
	(0.17)	(0.08)	(0.11)	(0.07)	[0.144]
pub_journal	0.365**	0.094	0.335***	0.104*	0.257***
	(0.15)	(0.07)	(0.10)	(0.06)	[0.113]
pub_english	−0.059	−0.022	−0.053	−0.028	−0.142
	(0.13)	(0.19)	(0.09)	(0.16)	[−0.064]
h_urban	0.137	0.241**	0.019	0.215**	0.377**
	(0.14)	(0.11)	(0.10)	(0.09)	[0.169]
h_nation	0.068	−0.053	0.041	−0.065	−0.277**
	(0.13)	(0.09)	(0.09)	(0.07)	[−0.109]
d_micro	0.033	−0.084	−0.037	−0.081	−0.461**
	(0.14)	(0.17)	(0.09)	(0.15)	[−0.225]
d_cross-section	−0.081	−0.213**	−0.199	−0.207**	−0.335**
	(0.19)	(0.10)	(0.13)	(0.09)	[−0.175]
d_pooled	0.462*	0.730***	0.050	0.302	0.122
	(0.24)	(0.26)	(0.16)	(0.24)	[0.057]
model_type	−0.148	−0.154	−0.146	−0.184	0.006
	(0.23)	(0.27)	(0.15)	(0.24)	[0.002]
model_rank2	0.021	0.063*	0.045	0.065**	0.018
	(0.11)	(0.03)	(0.08)	(0.03)	[0.008]
budget_stage	0.266*	0.244***	0.286***	0.245***	0.601***
	(0.15)	(0.09)	(0.10)	(0.08)	[0.279]
elasticity_inc	−0.577***	−0.629***	−0.577***	−0.624***	−1.465***
	(0.13)	(0.09)	(0.08)	(0.08)	[−0.678]
demographic	−0.223	−0.016	−0.083	−0.009	−0.045
	(0.16)	(0.07)	(0.11)	(0.06)	[−0.02]
sls_est	0.346	0.456	0.117	0.253	0.843*
	(0.34)	(0.36)	(0.23)	(0.33)	[0.629]
sur_est	0.397*	0.160	0.165	0.007	−0.423
	(0.21)	(0.30)	(0.15)	(0.27)	[−0.215]
ml_est	0.411*	0.184	0.188	0.030	−0.317
	(0.23)	(0.30)	(0.16)	(0.27)	[−0.126]
gmm_est	0.857**	0.329	0.645***	0.186	0.198
	(0.33)	(0.36)	(0.22)	(0.32)	[0.097]
other_est	0.029	0.144	−0.205	−0.026	−0.380
	(0.23)	(0.30)	(0.16)	(0.27)	[−0.14]
lnincome	−0.006	−0.009	0.024	−0.005	−0.127
	(0.07)	(0.04)	(0.05)	(0.03)	[−0.055]
Pork	1.820**	1.029***	2.212***	1.082***	1.417**
	(0.72)	(0.35)	(0.48)	(0.30)	[0.959]
Poultry	2.251***	0.744**	1.473***	0.666***	0.867*
	(0.64)	(0.30)	(0.43)	(0.26)	[0.449]
Beef & mutton	1.023	0.618*	1.671***	0.757**	0.847
	(0.73)	(0.37)	(0.48)	(0.32)	[0.549]
inter_pork	−0.197**	−0.118***	−0.245***	−0.125***	−0.166*
	(0.09)	(0.04)	(0.06)	(0.04)	[−0.073]
inter_poultry	−0.242***	−0.082**	−0.157***	−0.074**	−0.098
	(0.08)	(0.04)	(0.05)	(0.03)	[−0.043]
inter_beef & mutton	−0.102	−0.067	−0.171***	−0.082**	−0.092
	(0.09)	(0.04)	(0.06)	(0.04)	[−0.04]
Constant	0.331	0.835**	0.412	0.978***	1.431
	(0.65)	(0.35)	(0.43)	(0.31)	(0.88)
Theta (Θ)					−0.285
					(0.30)
Adjusted R^2	0.391	0.711	0.495	0.767	1.000
Sample Size	240	240	237	237	237

Standard errors are provided in parentheses, while marginal effects for the Box-Cox model (evaluated at sample means) are provided in brackets.
The dependent variable in each regression is the income elasticity.

*** 1% level of significance.

** 5% level of significance.

* 10% level of significance.

Table 5
Results of Vuong's test for non-nested model selection.

Comparison of Performance	Vuong *Z*-Statistic (unadjusted)	*p*-Value	Vuong Z-Statistic (adjusted)	*p*-Value
Cereals: WLS vs. Box-Cox	− 31.49	0.00	− 31.32	0.00
Meat: WLS vs. Box-Cox	− 33.33	0.00	− 33.20	0.00

A significant negative Z-statistic indicates that model 1 is rejected in favor of model 2.

5.2. Rural-urban differences

Controlling for per capita income, we do not detect statistically significant differences in income elasticities for cereals between rural and urban households. This suggests that the rural-urban differences for cereals in the summary statistics in Table 1 are due mainly to per capita income differences. On the other hand, income elasticities for meat products are higher in urban households even when per capita income is controlled. As noted above, urban households generally have access to a wider variety of food products than rural households, including processed and pre-prepared meat products, and have more restaurant options for dining out. In a study of urban Chinese households, Bai, Seale, Wahl, and Lohmar (2013) find that meat's share of food away from home (FAFH) expenditures is significantly greater than its share of food at home (FAH) expenditures. They also find that income elasticities for meat consumed away from home are greater than income elasticities for meat consumed at home. Zhou et al. (2015) find that the expenditure elasticity for FAFH is 1.39 in urban China, much higher than the other expenditure elasticities. Their results may provide an explanation for our findings.

Yu and Abler (2016) point out the difference between consumption household size and survey household size. Due to off-farm employment in rural China, the survey household size which is often used in econometric practice is larger than the consumption household size. This could lead to downward bias in both per capita food consumption and income elasticities in terms of absolute values.

5.3. Results for other variables

5.3.1. Regional vs. national data

The use of national data (as opposed to data for specific regions of China) is associated with higher income elasticities for cereals but lower income elasticities for meat products. As noted above, most of the regional studies were conducted in more developed areas of China. These results may be due to access to a wider variety of food products in the richer eastern provinces, including various types of meat products. As a result households in these provinces may be more likely than households elsewhere in China to consume alternatives to cereals, including meat, as their incomes increase.

5.3.2. Micro vs. aggregate data

The use of micro data (as opposed to aggregate data) does not have a statistically significant impact on income elasticities for cereals, but it is associated with lower income elasticities for meat. Micro survey data are often collected in a single city in which the availability of meat is similar for survey respondents at different income levels. Aggregate data are typically provincial-level data, and as a province becomes wealthier retailers are likely to find it profitable to offer a greater variety of meats for sale. Comparisons of meat consumption across provinces capture both genuine income effects at the household level and changes in meat availability at the market level.

5.3.3. Income vs. expenditure

The results indicate that studies using total income as their measure of income have smaller income elasticities than those using total expenditure. The marginal effect for the total income dummy is − 0.409 and − 0.678 for cereals and meat, respectively. By definition, total income equals total expenditure plus net savings. If the savings rate increases as income increases (Dynan, Skinner, & Zeldes, 2004), then demand elasticities with respect to total income must be lower than elasticities with respect to total expenditure.

5.3.4. Cross-sectional vs. panel data

Compared with panel data, the estimated coefficients for the cross-section dummy variable are 0.206 and − 0.335 for cereals and meat, respectively, and both are statistically significant. This suggests that the type of data does matter for income elasticity estimates, although its impact varies by product.

5.3.5. Budgeting process

Compared with multi-stage budgeting, the estimated coefficients for the single-stage dummy are 0.015 and 0.601, respectively, for cereals and meat; and only the latter is statistically significant. This implies that multi-stage budgeting yields lower income elasticities for meats. This may be due to the fact that a multi-stage budgeting assumption restricts the flexibility of consumption to adjust to income changes.

Table 6
Estimated and Projected Income Elasticities, 2000–2030.
Source: Authors' calculations based on meta-regression results and assumptions described in text.

		2000	2010	2020	2030
Rural	General cereals	0.507	0.373	0.278	0.212
	Wheat	0.475	0.517	0.553	0.582
	Rice	0.530	0.483	0.446	0.418
	Coarse grains	0.399	0.337	0.291	0.256
	General meat	0.435	0.396	0.366	0.345
	Pork	0.486	0.389	0.326	0.286
	Poultry	0.475	0.400	0.349	0.314
	Beef & mutton	0.486	0.411	0.359	0.324
	Per capita income (Yuan, 2012 prices)	2253	5919	13,201	25,014
Urban	General cereals	0.310	0.194	0.130	0.087
	Wheat	0.452	0.499	0.533	0.562
	Rice	0.416	0.369	0.338	0.313
	Coarse grains	0.281	0.223	0.187	0.159
	General meat	0.532	0.474	0.439	0.412
	Pork	0.517	0.399	0.337	0.295
	Poultry	0.536	0.437	0.383	0.344
	Beef & mutton	0.551	0.452	0.396	0.357
	Per capita income (yuan, 2012 prices)	6280	19,109	40,961	77,615
National	General cereals	0.403	0.266	0.174	0.119
	Wheat	0.462	0.511	0.553	0.585
	Rice	0.471	0.419	0.379	0.350
	Coarse grains	0.337	0.272	0.223	0.190
	General meat	0.477	0.426	0.388	0.363
	Pork	0.499	0.383	0.312	0.271
	Poultry	0.501	0.409	0.348	0.310
	Beef & mutton	0.514	0.421	0.359	0.321
	Per capita income (Yuan, 2012 prices)	3712	11,590	29,857	59,731

5.3.6. Demand system and demographic controls

When it comes to the functional form of the demand model, the only statistically significant variable is the use of a demand system for cereals. Compared with pragmatic (or ad hoc) models, demand systems derived from economic theory tend to yield smaller income elasticities for cereals. Demand systems require the imposition of constraints in order to be consistent with economic theory, including adding up, homogeneity, and symmetry. Those restrictions appear to have some impact on estimated income elasticities. We find that the model's rank does not have a statistically significant influence on estimated income elasticities. Our results also indicate that whether or not a demand model includes demographic factors has no statistically significant impact on estimated income elasticities.

5.3.7. Estimation procedure

Most of the coefficients for the estimation methods (OLS, 2SLS, etc.) are not statistically significant. The only statistically significant results are for 2SLS for cereals and meat, and GMM for cereals. It seems that the estimation procedure does not matter much in terms of estimated income elasticities.

5.3.8. Publication bias

The results provide some evidence of publication bias. Compared to studies published as book chapters or non-refereed reports, the marginal effect for working papers is 0.385 and is statistically significant. For meats, the marginal effects for working papers and peer-reviewed journals are 0.144 and 0.113, respectively, and both are statistically significant. In addition, we find that income elasticities for cereals in English-language studies are significantly lower than those in Chinese-language studies. Larger elasticities in Chinese-language studies might arise from the use of different primary study designs or differences in access to data sources.

6. Projecting income elasticities and demands

Our results can be used to project income elasticities for China. Table 6 presents estimates of income elasticities for 2000 and 2010, and projections for 2020 and 2030. The estimates for 2000 and 2010 are based on real per capita incomes in those years, while the projections for 2020 and 2030 assume a real per capita income growth rate of 6.6% per year from 2012 onward (2012 was the most recent year at the time this paper was written that per capita income statistics were available from NBSC). The 6.6% figure is based on projections by the World Bank (2013), in a report written in partnership with China's Development Research Center of the State Council (DRC). This figure is similar to OECD's (2012) projection of 6.4% per year for 2011–2030. Due to differences between rural and urban households, we estimate and project income elasticities for rural and urban households separately. We then obtain national level figures by taking a population-share weighted average of the rural and urban figures. For 2020 and 2030, we use the urbanization rates projected by the DRC, which are 60% in 2020 and 66% in 2030 (China Youth Daily, 2013).

The figures in Table 6 indicate that national-level income elasticities for general cereals and general meat were 0.40 and 0.48, respectively, in 2000 and that they are projected to decline to 0.12 and 0.36, respectively, by 2030. The income elasticity for wheat is projected to rise from 0.46 to 0.59 over this time period, while income elasticities for all other products are projected to decline. As with the summary statistics in Table 1 and the meta-regression results in Table 3, the figures in Table 6 reveal some inconsistencies between the general cereals and meats categories and the individual products that make up these categories. For example, the elasticities for pork, poultry, and beef & mutton are each greater than the elasticity for general meat in 2000, while each is less than the elasticity for general meat in 2010, 2020, and 2030. As noted above, the income elasticity for a group should in theory be a weighted average of the income elasticities for the products in that group. But as also noted earlier, the elasticity estimates for each product come from different sets of studies with different results.

Bearing this in mind, the downward trend for all products except wheat is plausible. Cereals and meat products are the major calorie sources for Chinese consumers (Tian & Yu, 2013; Yu & Abler, 2009). As income grows, caloric intakes are reaching a saturation point for most Chinese consumers, and obesity and chronic diseases associated with obesity are becoming public health problems (Tian & Yu, 2013). In the case of wheat, our results are consistent with the westernization of Chinese diets and the associated demand for high-protein wheat (Bai et al., 2014).

There are many models of global food and agricultural markets used to make projections for China and other countries, including the OECD-FAO AGLINK-COSIMO model, USDA's baseline projections modeling system, the Food and Agricultural Policy Research Institute's (FAPRI) suite of international models, and IFPRI's IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade) model. In general, demand elasticities in these models do not change over time. Fan and Agcaoili-Sombilla (1997) note that the values of demand and supply parameters could be a major reason for heterogeneities in food consumption projections in the current literature, in addition to model structure and macro assumptions. While we are not able to re-run these models with time-varying income elasticities of demand for China, we can examine how much of a difference this would make to the magnitudes of the shifts in food demand curves caused by per capita income growth.

For this exercise, we use UN (2014) population projections and assume that China's population will increase from 1.36 billion in 2010 to 1.45 billion in 2030, with annual population growth rates of 0.61% during 2010–2015, 0.44% during 2015–2020, 0.22% during 2020–2025, and 0.06% during 2025–2030. We start with 2012 levels of FSI (food, seed and industrial) consumption in China from the USDA/Foreign Agricultural Service (2014) PS&D database.[1] We then project consumption forward based on real per capita income growth, income elasticities, and population growth. Prices are assumed to remain constant in this exercise. Of course prices would change over time in response to demand and supply shifters, but the purpose of the exercise is to compare the magnitudes of shifts in demand curves, not changes in market-equilibrium quantities.

The results of this exercise for general cereals, rice, wheat, general meat, and pork are shown in Table 7. Pork is the predominant meat consumed in China, and specifically more than 60% of the meat consumed in China is pork (Yu & Abler, 2014). The projections based on constant income elasticities are higher than those time-varying projections except for wheat, which is lower. It comes as no surprise that the differences between consumption values based on time-varying income elasticities and values based on constant elasticities increase over time. By 2030, the percentage differences between the two sets of values are about 11.5% for general cereals, 4.9% for rice, 4.9% for wheat, 4.5% for general meat, and 8.7% for pork. Even though the percentage differences might seem small, particularly for rice and meat, the quantity differences are fairly large, given the sheer size of China's consumption. The quantity differences by 2030 are about 45.9 million tons for general cereals, 11.6 million tons for rice, 12.2 million tons for wheat, 5.4 million tons for general meat, and 6.9 million tons for pork. Given the tight domestic food supply situation in China, incorrect projection could lead to inappropriate agricultural and trade policies that could distort world food markets. It would be advisable to use time-varying income elasticities for consumption projections, especially when gauging long-term consumption.

7. Conclusions

This study performed a meta-analysis of income elasticity estimates for meat and cereal products in China using a collection of 143 and 240 income elasticity estimates for cereals and meat products, respectively, from 36 primary studies, and used the results to project income elasticities of demand for these products to 2030. We find that income elasticities for all meat products (general meat, pork, poultry, beef & mutton) tend to decline as per capita income increases. The income elasticity for pork, the most important meat product consumed in China, declines faster with per capita income growth than the elasticity for the meat group as a whole. We also find this is true for most cereals (general cereals, rice, and coarse grains) with the exception of wheat. The income elasticity of demand for wheat increases as per capita income increases, which may be due to the westernization of Chinese diets and the associated demand for high-protein wheat (Bai et al., 2014).

Our results indicate that urban-rural differences do not have a statistically significant impact on income elasticities for cereals, after controlling for per capita income differences between rural and urban areas. However, income elasticities for meat products are significantly higher for urban households than for rural households. This may be due to the fact that urban households have more restaurant options for dining out than rural households, and evidence that meals eaten away from home are more likely to include

[1] Food consumption is not broken out separately from total FSI consumption in the PS&D database, but the differences between food and FSI consumption for China would be small, even in the case of coarse grains considering the fact that China's biofuel industry is small. Meyer and Yu (2011) used Monte-Carlo simulations to show the differences between different demand models.

Table 7
Alternative food consumption levels for 2030 (million tons).
Source: authors' calculations based on meta-regression results and assumptions described in text.

Year	Based on Constant 2010 Elasticities					Based on Time-Varying Elasticities				
	General cereals	Rice	Wheat	General meat	Pork	General cereals	Rice	Wheat	General meat	Pork
2012	310.2	144.0	125.0	71.9	52.7	310.2	144.0	125.0	71.9	52.7
2015	332.2	158.8	140.3	79.4	57.7	329.3	158.3	140.8	79.1	57.3
2020	369.6	185.6	168.8	93.0	66.7	357.9	183.1	171.2	91.8	65.1
2025	407.0	214.8	201.1	107.8	76.3	381.1	208.7	207.1	105.0	72.5
2030	445.3	246.9	238.1	124.1	86.7	399.5	235.3	250.3	118.8	79.8

meat than meals eaten at home (Bai et al., 2013).

Our results indicate that national-level income elasticities for general cereals and general meat were 0.40 and 0.48, respectively, in 2000 and that they are projected to decline to 0.12 and 0.36, respectively, by 2030. The income elasticity for wheat is projected to rise from 0.46 to 0.59 over this time period, while income elasticities for all other products are projected to decline. These changes in income elasticities are large enough that models used to make long-term projections of Chinese food consumption should incorporate time-varying income elasticities of demand. Given the tight domestic supply of food products in China, incorrect projections could lead to inappropriate agricultural and trade policies that could distort world food markets.

Appendix A. List of primary studies

Authors	Where Published or Released	Publication/ Release Date	Rural or urban	Data	Product category	Mean Income Elasticity
Cater and Zhong	AJAE	1999	Rural	Pooled	Cereals	− 0.170
Chern and Wang	CER	1994	Urban	Pooled	Cereals	0.071
					Meat	1.561
Fan et al.	AJAE	1995	Rural	Pooled	Cereals	0.510
					Meat	0.900
Gale and Huang	Report	2007	Rural	Pooled	Cereals	0.060
					Meat	0.430
			Urban	Pooled	Cereals	− 0.090
					Meat	0.220
Gao, Wailes and Cramer	AJAE	1996	Rural	Cross-section	Cereals	0.625
					Meat	0.792
Halbrendt, Tuan, Gempesaw and Dolk-Etz	AJAE	1994	Rural	Cross-section	Cereals	0.575
					Meat	1.183
Han and Wahl	JAAE	1998	Rural	Cross-section	Cereals	1.115
					Meat	0.421
Han, Cramer, and Wahl	Working paper	1997	Rural	Cross-section	Cereals	1.139
					Meat	0.510
He, Chidmi, and Zhou	Working paper	2011	Urban	Panel	Cereals	0.371
					Meat	1.337
Hovhannisyan and Gould	Working paper	2010	Urban	Cross-section	Cereals	0.267
					Meat	0.278
Huang and Gale	CAER	2009	Urban	Panel	Cereals	− 0.065
					Meat	0.348
Jiang and Davis	AE	2007	Rural	Panel	Cereals	0.655
					Meat	0.817
Lewis and Andrews	JAE	1989	Rural	Pooled	Cereals	0.220
					Meat	1.485
			Urban	Pooled	Cereals	0.340
Liu and Chern	Working paper	2003	Urban	Cross-section	Cereals	0.657
					Meat	0.736
Shono et al.	Book	2000	Urban	Cross-section	Cereals	0.080
					Meat	0.543
Wu, Li, and Samuel	AE	1995	Urban	Cross-section	Cereals	0.980
					Meat	1.170

Yan	Dissertation	2007	Rural	Cross-section	Cereals	0.494
					Meat	0.825
Ye and Taylor	EDCC	1995	Rural	Cross-section	Cereals	0.176
					Meat	0.534
Zhang and Wang	Working paper	2003	Urban	Cross-section	Cereals	0.393
					Meat	0.271
Zhang, Mount, and Boisvert	ARER	2001	Rural	Panel	Cereals	0.206
					Meat	0.537
Zheng	Dissertation	2008	Urban	Cross-section	Cereals	0.199
					Meat	0.267
Zheng and Henneberry	JAAE	2010	Urban	Cross-section	Cereals	0.214
Zheng and Henneberry	JARE	2010	Urban	Cross-section	Cereals	0.136
					Meat	0.404
Chen	Chinese	2010	Rural	Cross-section	Meat	0.752
			Urban	Cross-section	Meat	0.249
Chang and Li	Chinese	2006	Rural	Cross-section	Cereals	0.072
Li	Chinese	1995	Rural	Cross-section	Cereals	0.216
Li and Yang	Chinese	2001	Rural	Cross-section	Cereals	0.166
					Meat	0.300
			Urban	Cross-section	Cereals	0.133
					Meat	0.438
Liu and Zhong	Chinese	2009	Urban	Cross-section	Cereals	0.294
					Meat	0.376
Liu	Chinese	2010	Urban	Cross-section	Meat	0.386
Mu	Chinese	2001	Rural	Panel	Cereals	0.658
					Meat	1.352
			Urban	Panel	Cereals	0.606
					Meat	1.294
Qu and Huo	Chinese	2007	Rural	Cross-section	Cereals	0.872
					Meat	1.141
Zhang et al.	Chinese	2004	Rural	Cross-section	Cereals	0.070
					Meat	0.250
Zheng and Henneberry	RAE	2009	Urban	Cross-section	Cereals	0.795
					Meat	1.021
Zheng and Henneberry	Agribusiness	2011	Urban	Cross-section	Cereals	0.118
					Meat	0.238

The mean income elasticity (last column) is the mean of the income/expenditure elasticities reported by a study for the indicated product category (next-to-last column).

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