Dynamic Food Demand in China and International Nutrition Transition

Dissertation
to obtain the Ph. D. degree
in the International Ph. D. Program for Agricultural Sciences in Goettingen (IPAG) at the
Faculty of Agricultural Sciences,
Georg-August-University Göttingen, Germany

presented by

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born in Sichuan China

Göttingen, May, 2014

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Date of dissertation: 22.05.2014

Acknowledgment

My PhD. Study is sponsored by the Research Training Group 1666 of German Research Foundation (DFG). I would like to thank it for providing the financial support for my study and living in Germany.

During my whole Ph.D. study, I have received multifaceted supports form my colleagues and friends. First and foremost, I would like to express my gratitude to my supervisor Professor Xiaohua Yu for his countless help. I would like to thank him for inviting me to study in Goettingen. Professor Yu taught me many useful analytic tools in academia and led me to completing my researches. His supervision and selfless supports during my study are greatly appreciated. I am also grateful to him for his valuable ideas and inputs in my dissertation. I also would like to thank my co-advisor Professor Dr. Thomas Herzfeld for his comments on my research. My further thanks would go to Professor David Abler, Professor Dr. Matin Qaim and Professor Dr. Berhnard Breummer for their help in my research.

My colleagues Dr. Xu Tian, Dr. Rainer Holst, Dr. Stefan Meyer, Hanna Ihli, Nico Herforth etc., also gave me lots of help and shared many good ideas and wonderful experiences with me during my stay in Goettingen. I am really grateful for their good deeds. My research assistant Larissa Wood took her time to polish my research, and, herein, I would like to appreciate her great work.

I am also grateful to my girlfriend Miss Sirimaporn Leepromrath for her thoughtfulness, understanding and support. Finally, I wish to express my deep gratitude to my parents and my brother for their supports in past years.

De Zhou

May 2014, Goettingen

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Abbreviation and Acronyms

2SLS: two-stage least squares

AIC: Akaike information criterion

AIDS: almost ideal demand system

BIC: Bayesian information criterion

CNKI: China National Knowledge Infrastructure

CNY: Chinese Yuan

CPI: consumer price index

DLES: dynamic linear expenditure system

DRC: China Development Research Center of the State Council

FAO: Food and Agriculture Organization of the United Nations

FAPRI: Food and Agricultural Policy Research Institute

FMM: finite mixture model

GMM: generalized method of moments

GNP: gross national product

IFPRI: International Food Policy Research Institute

LA/DAIDS: linear approximate dynamic almost ideal demand system

LES: linear expenditure system

ML: maximum likelihood

NBSC: National Bureau of Statistics of China

OECD: Organisation for Economic Co-operation and Development

OLS: ordinary least squares

PPP: purchasing-power parity

QUAIDS: quadratic almost ideal demand system

SUR: seemingly unrelated regression

UHS: China urban household surveys

UN: United Nations

USD: United States Dollar

USDA: United States Department of Agriculture

WB: World Bank

WLS: weighted least squares

Executive Summary

Economic growth followed by urbanization and food supply modernization in developing countries would lead to substantial changes in food demand. Global agri-food systems are undergoing a rapid transformation towards high-value and high-quality products. China would be a good and important example. The rapid economic growth has led substantial changes in food consumption. Chinese consumers substantially increased their consumption of meat, dairy products and fruits and pay more attention to food quality. In conjugation with economic growth, consumers are experiencing nutrition transition due to the changes in food consumption patterns, especially in the emerging countries. Those transformations in agri-food systems need to be understood with a view to agricultural and food policies. And an analysis of the changes in food consumption is the corner stone for demand projections and poverty demolishing.

Hence, it is of great importance to deepen our understanding of dynamics in food demand and the consequences for nutrition transition with income growth. This dissertation carries out three studies on dynamic food demand and its consequences for nutrition transition. Specifically, there are three topics investigated in this dissertation as follows: to propose a dynamic demand system to capture the consumption behavior in dynamic food demand process; to evaluate the dynamics and heterogeneities in income elasticities, and then to project China's food consumption in the future; to illustrate transitions of nutrition consumption as the economic growth and food consumption changes.

In a first step this dissertation aims at analyzing food demand in dynamic process. Consumers may not simultaneously adjust their behavior to changes in income in the short-run, confined by the adjusting costs, such as habit formation, switching cost, and learning cost etc. The existence of adjusting costs implies that static demand models in the current main stream literature might not correctly model consumer behaviors. Specifically, the income or expenditure elasticities estimated by these static models might be over-reported. It could lead to serious policy consequence if these elasticities are used for projection. The first case study investigates dynamic food demand in urban China herein. With an adoption of transitionary demand process, a new approach of complete demand system with a two-stage dynamic budgeting system (DLES- LA/DAIDS) is developed, including an additively separable dynamic linear expenditure system (DLES) in the first stage and a linear approximate dynamic almost ideal demand system (LA/DAIDS). Employing provincial aggregate data (1995-2010) from the China urban household surveys (UHS), the estimates of the demand elasticities for primary food products in urban China are carried out.

The results indicate that most primary food products, including grains, edible oils, meat, poultry and vegetables, are necessities and price-inelastic for urban households in China. In the dynamic model, the assumption of simultaneously full adjustments, which is adopted in static models, is abolished due to adjusting costs (e.g. consumer expectation, habit formation, and learning/switching costs). Therefore, the results from different models would vary from each other. Comparing with the results from some static models, the results indicate that the dynamic model tends to yield relatively smaller expenditure elasticities in magnitude than the static models do. As this research methodologically relaxes the restrictive assumption and allows consumers to make dynamic decisions in food consumption, it can be used for better projections in policy simulation models.

Since demand elasticity is critical for gauging the growth of food demand, its accuracy and credibility are very important. However, it is a tough job to evaluate the elasticities and demand projections from a large volume of empirical studies on food demand in China, as they usually vary widely from each other. In a second step, a meta-analysis of the income elasticity of food demand in China is preformed, using of 143 elasticities for cereals and 240 for meat collected from 36 primary studies. The further projections of demand elasticities and food consumption are estimated based on the results of meta-regressions.

The study finds that income elasticities vary across products in both the cereals and meat groups. The elasticities for all meat (general meat, pork, poultry, beef & mutton) and cereal products (general cereals, wheat, rice, coarse grain), except for wheat, tend to decline with income growth. The results also indicate that urban-rural differences do not have a statistically significant impact on income elasticities for cereals after controlling for the differences in income between rural and urban areas. Moreover, the type of data (cross section, pooled, panel), publication source, budgeting process, demand models and the use of household expenditure as the measure of income in a study have significant impacts on the reported income elasticities in China after controlling for product differences.

With the assumptions on urbanization rates projected by the DRC(China Development Research Center of the State Council), population growth rates indicated by the UN and per capita income growth rates of 6.6% per year from 2012 onward (OECD projection), the projections of income elasticities for main food products for a few selected years are also worked out. The income elasticities for cereals and meat are projected to be 0.40 and 0.48 respectively at the national level in 2000, and those elasticities slide to 0.12 and 0.36 in 2030. Taking the dynamics in elasticities into account, the projections based on constant income elasticities usually are higher than those time-varying projections except for wheat. Specifically, the dynamically projected demand for cereal and meat will reach to 623.82 and 121.98 million tons respectively in 2030 in China, and the consumption of cereal and meat grows at the speed of 1.45% and 3.05% respectively in 2012-2030. The static projections are about 45.9 million tons for general cereals and 5.4 million tons for general meat higher by 2030. Given the tight domestic food supply situation in China, models used to make long-term consumption projections should incorporate time-varying income elasticities.

In conjugation with the income growth, the changes of food consumption pattern usually lead to a nutrition transition. In a third step, the impact of income growth on nutrition transition is investigated. When income is very low, consumers tend to buy the cheapest food such as cassava, wheat and rice which are also cheap sources of calories. As income grows, consumers usually pay more attention to non-calorie attributes, rather than merely pursuing additional calories. The third case study proposes a finite mixture model (FMM) to identify the behavioral transition of calorie consumption with an assumption that nutrition consumption is a mixture of different behaviors in two stages: a hunger stage and an affluent stage.

Based on 381 calorie-income elasticities collected from 90 primary studies, the results indicate that the calorie-income elasticity generally moves downwards as income grows, but the relationship between calorie-income elasticity and income varies across different stages. The threshold income for calorie demand transition is 459.8 USD in 2012 prices (PPP), namely 1.26 dollar/day, which is consistent with the World Bank's poverty line (1.25 dollar/day in 2005 PPP prices). In the poor stage, the income elasticity declines rapidly. The results indicate that when income increases by 10%, the calorie income elasticity would decrease by 0.012. Once consumers reach the affluence stage, food choice becomes more complicated and a further increase of income will have no significant impact on calorie-income elasticity as non-nutritional attributes play important roles.

1 Introduction

Food consumption patterns have been underpinned by economic development and income growth. The development of urbanization and modernization of food supply chain associated with economic growth would lead to substantial changes in food demand. And global agri-food systems are undergoing a rapid transformation towards high-value and high-quality. It has already largely occurred in developed countries, while continuing strongly many emerging economies (Abler, 2010). As consumers dynamically adjust food consumption and change consumption patterns as income grows, the income elasticity also changes. Moreover, consumers are experiencing nutrition transition due to those changes in food consumption, especially in the emerging countries. Given the prominent implications for food demand projections and poverty demolishing, it is very important to deepen our understanding of dynamics in food demand and the consequences for nutrition transition with a view to agricultural and food policies (Timmer, 2009).

Therefore, there are several questions highly interested in this dissertation as follows: how to capture the consumption behavior in dynamic food demand process; how to evaluate a set of estimates for income elasticities, and then to project the food consumption in the future; what happens in the nutrition consumption as the economic growth and food consumption changes. In order to answer those questions, this dissertation carries out three case studies on the dynamic food demand and its consequences for nutrition transition. More specific details will stream out in following sections.

1.1 Dynamic Food Demand in China

Considering the driving forces of demand transformation, China would be a good and important example to understand how rapid economic growth and other fundamental factors shape the structures of food demand and further corresponding impacts, as China has over one-fifth of the world's population and has been one of the most successful economies with average growth rates of more than 8% in the past three decades (Zheng and Henneberry, 2009; Yu and Abler, 2009). The rapid economic growth has led to an increasing urbanization and a rapid growth in the number of supermarkets, convenience stores and outlets (Gale and Huang, 2007). And it has great impacts on food consumption. The importance of staple grains and low-quality vegetables has been diminishing significantly. Chinese consumers substantially increased their consumption of meat, dairy products and fruits and also pay more and more attention to food quality (Fan *et al.*, 1994; Yu and Abler, 2009).

The obvious evidences are that Chinese rural households which are about 60% of total population shrunk the per capita annual grain consumption from 262.08 kg in 1990 to 164.27 kg in 2012 (Table 1-1). Similar trend is detected in the urban area, and per capital grain consumption dropped from 130.72 kg to 78.76 kg over the same period (China Statistic Yearbook 2008). At the same time, Chinese consumers substantially increased their consumption of meat, dairy products, and fruits (Fuller and Dong, 2006). For instance, the per capita consumption of milk increased from 4.63 kg to 13.95 kg in 1990-2012 in urban area and it grew even faster in rural area.

Table 1-1 Per capita consumption of major foods in China

Item	1990	1995	2000	2005	2010	2011	2012
Urban Household							
Grains	130.72	97.00	82.31	76.98	81.53	80.71	78.76
Vegetables	138.70	116.47	114.74	118.58	116.11	114.56	112.33
Vegetable Oil	6.40	7.11	8.16	9.25	8.84	9.26	9.14
Pork	18.46	17.24	16.73	20.15	20.73	20.63	21.23
Beef and Mutton	3.28	2.44	3.33	3.71	3.78	3.95	3.73
Poultry	3.42	3.97	5.44	8.97	10.21	10.59	10.75
Aquatic Products	7.69	9.20	11.74	12.55	15.21	14.62	15.19
Eggs	7.25	9.74	11.21	10.40	10.00	10.12	10.52
Milk	4.63	4.62	9.94	17.92	13.98	13.70	13.95
Fruits	41.11	44.96	57.48	56.69	54.23	52.02	56.05
Rural Household							

Item	1990	1995	2000	2005	2010	2011	2012
Grains	262.08	256.07	250.23	208.85	181.44	170.74	164.27
Vegetables	134.00	104.62	106.74	102.28	93.28	89.36	84.72
Vegetable Oil	3.54	4.25	5.45	4.90	5.52	6.60	6.93
Pork	10.54	10.58	13.28	15.62	14.40	14.42	14.40
Beef and Mutton	0.80	0.71	1.13	1.47	1.43	1.90	1.96
Poultry	1.25	1.83	2.81	3.67	4.17	4.54	4.49
Aquatic Products	2.13	3.36	3.92	4.94	5.15	5.36	5.36
Eggs	2.41	3.22	4.77	4.71	5.12	5.40	5.87
Milk	1.10	0.60	1.06	2.86	3.55	5.16	5.29
Fruits	5.89	13.01	18.31	17.18	19.64	21.30	22.81

Source: China Statistic Yearbook 2013

Note: For rural households, fruits include fresh fruits and processed products, grain is unprocessed, and milk includes fresh milk and processed products.

These changes in food demand have drawn increasing interests. There is plenty of literature on the estimation of food demand in China with different methods, such as Lewis and Andrews (1989), Fan et al. (1995), Wang and Jensen (1994), Wang et al. (1995), Wu et al. (1995), Dong and Capps (1998), Fang and Beghin (2002), Ma et al. (2004), Wan (2005),Yen et al. (2004), Liao and Chern (2007), Gale and Huang (2007), Yu and Abler (2009), Zheng and Henneberry (2009) and so on. Most of analyses mainly focus on statically estimating price and income elasticities for food aggregates. The common demand models adopted in current literature are linear expenditure system (LES), almost ideal demand system (AIDS), and quadratic almost ideal demand system (QUAIDS), which are typical static models.

In static models, some restrictive assumptions are needed to simplify the empirical analysis. One of them is that consumer demand within each period depends on total expenditure and price for that period alone (Deaton, 1986). However, it's widely accepted that, for most consumers, food demand will be influenced largely by the habit persistence, learning process and the cost of changing consumption patterns (Brown, 1952; Lamm, 1982). Nevo (2010) summarized that the exact effect of dynamic differs can be generated for several reasons, including storable products, durable products, habit formation, switching costs and learning process. And neglecting of dynamic differs would lead to doubtfully high demand elasticities (Shukur, 2002).

Herein, it is more reasonable to assume that food demand is dynamic process in the sense that (a) past consumption influences current preferences and demand or higher level of past consumption of a food implies a higher level of present consumption of that food; (b) consumers' current decisions affect their future utility, or consumers' current decisions depend on expectations about the evolution of future states; (c) any changes in consumer behavior encounter the learning process and switching cost. Therefore, the existing demand models are not well suited to capture demand dynamics in China as high-value products are increasingly substituting for staple food. And there is a need to develop a new approach to model dynamic consumption behavior in China.

Therefore, one purpose of this dissertation is to employ a transitionary demand process and to develop a new approach of complete demand system with a two-stage dynamic budgeting: an additively separable dynamic linear expenditure system (DLES) in the first stage and a linear approximate dynamic almost ideal demand system (LA/DAIDS) with the inherent of weak separability in the second stage. More details about the methodological background and an overview of the empirical findings are introduced in sections 1.4.1 and 1.5.1. The complete study is contained in chapter 2.

1.2 Dynamics in Income Elasticities and Consumption Projections in China

The primary task of modeling food demand is to get demand elasticities. Income elasticities have prominent implications for projecting food consumption. Hence, the accuracy and credibility of income elasticities are critical in market simulation process, especially when consumers are experiencing substantial economic growth in the case of China. As aforementioned, consumers change their food consumption patterns as income increases and demand behavior is a dynamic process rather than a static one. There are some literature evidences that income elasticities also dynamically change with income growth.

Therefore, it is of great importance to understand dynamics in income elasticity and how it dynamically changes with income growth in long term. However, the essential part of this issue is unrevealed in the current literature.

Moreover, there are extensive empirical studies on food demand in China using a wide range of models and data sources during the past two decades. However, the estimated demand elasticities and consumption projections yielded by the current literature are quite varied, and some even controversial (Abler, 2010). For instance, the income elasticity for wheat reaches 1.1 from the study of Han *et al.* (1997), much higher than -0.37 estimated by Carter and Zhong (1999). It is a tough job to evaluate the elasticities and demand projections from those studies. Thus, there is a need for a synthesis of existing research to scrutinize the heterogeneities and dynamics in current estimated demand elasticities and to determine a reasonable set of estimates for these elasticities, and then to project the food consumption in the future in China. To fill this gap, a meta-analysis of income elasticities for main food (cereals and meat) consumption in China is performed. With the results of meta- regressions, a set of demand elasticities for cereal and meat was projected. Moreover, the projections of cereals and meat demand in the near future were also provided based on the set of projected income elasticities and several assumptions. In Section 1.4.2 and 1.5.2, the methodological background and a brief overview of the empirical results of this study are introduced respectively. Chapter 3 presents the complete study on dynamics in income elasticities and China's consumption projections.

1.3 Nutrition Transition and Dynamic Calorie-Income Elasticities

In conjugation with the income growth, consumers are experiencing nutrition transition due to the changes in food consumption patterns, especially in the emerging countries. There is an abundance of nutrition literature on the relationship between income and calories consumption and how income growth could help reduce undernutrition in the long term

(Salois et al., 2012; Tian and Yu, 2013). Particularly, calorie-income elasticities draw a lot of attention to policy implications, as they indicate the impact of further income growth on calorie consumption. However, the results in the current literature are quite heterogeneous. Estimated calorie-income elasticities range from near zero (e.g. Behrman and Wolfe, 1984; Behrman and Deolalikar, 1987; Behrman *et al.*, 1997; Bouis, 1994; Salois *et al.*, 2012etc.) to almost one (e.g. Pitt, 1983; Strauss, 1984; Behrman *et al.*, 1997etc.). Even through Ogundari and Abdulai (2013) conducted a meta-analysis of 40 empirical nutrition demand studies to show a comprehensive review of the heterogeneity in calorie-income elasticities in the current literature, the linkage between income and calorie- income elasticities is not well scrutinized in the current literature. There is still a debate on the dynamics of calorie consumption in connection to income growth. Generally speaking, as income grows, consumers tend to increase calorie consumption, but the marginal growth rate tends to decline when the calorie intake approaches the saturation point and consumers shift to higher value and quality food (Gao *et al.*, 1996; Yu and Abler, 2009). Consequently, one can generally expect that income elasticities for calorie move downwards (Subramanian and Deaton, 1996; Skoufias, 2003; Yu and Abler, 2009; Skoufias *et al.*, 2011; Salois *et al.*, 2012; Jensen and Miller, 2010).

Jensen and Miller (2010) argue that consumers may show two different behavior patterns of food consumption with income growth and the relationship between increases in food expenditure and calorie intake is not linear. When income is very low, consumers stay at the subsistent level, suffering from hunger and undernutrition due to limited budgets, and so they tend to buy the cheapest food such as cassava, wheat and rice which are also cheap sources of calories. Once they surpass the subsistent-level, calorie intake soon gets saturated due to biological reasons. Consumers pay more attention to non-calorie attributes, rather than merely pursuing additional calories, and the calories elasticity rapidly declines to a very low level and stays inactive.

Therefore, one other purpose of this dissertation is to contribute the literature on dynamics in calorie-income elasticities with nutrition transition. Sections 1.4.3 and 1.5.3 present contain a brief introduction of the method and empirical findings in this study. The complete study on the impact of income growth on nutrition transition is presented in Chapter 4.

1.4 Methodology

1.4.1 Complete Two-Stage Dynamic Demand System: DELS-AL/DAIDS

There are some demand models have been developed and widely used in demand analysis, such as the Linear Expenditure System (LES) (Stone, 1954), the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980a), the Generalized Almost Ideal and Translog Demand Systems (GAITL) (Bollino and Violi, 1990), the Quadratic AIDS (Banks *et al.*, 1997). And most of those models are static demand models with a restrictive assumption that the food demand within one period only depends on the expenditure and prices in that period (Deaton, 1986). However, many studies indicate that consumers do not simultaneously make the adjustment to income or price changes and get a balance in a transitionary process (Brown, 1952; Pollak, 1970; Kesavan *et al.*, 1993; Anderson and Blundell, 1983; Blundell, 1988; Yu and Abler, 2010). It implies that food demand is a dynamic process rather than a static one.

To focus on the dynamic food demand, a complete demand system with a two-stage dynamic budget is proposed, which can replicate the decision making process and allow dynamic adjustments in consumption behavior. With the adoption of vector time series approach, the broad group allocation depends on the prices and expenditure both in the past and current periods. Then consumers allocate the expenditure on a subgroup in the following second stage. Regarding the function forms, the two-stage dynamic demand system includes an additively separable dynamic linear expenditure system (DLES) in the first stage and a linear approximate dynamic almost ideal demand system (LA/DAIDS) in the second stage.

In a typical vector time series model, the direct introduction of lagged demand leads to estimations of only short-run parameters (Bewley and Fiebig, 1990; Kesavan *et al.*, 1993). It is awkward to solve the standard estimators of the long-run responses as they involve ratios of regression coefficients. With Bewley's structural transformation (Bewley and Fiebig, 1990), the general DLES- LA/DAIDS is proposed, one could estimate both short-run and long-run elasticities. It is worthy to point out that the short-run elasticities may not satisfy the demand properties, such as symmetry and homogeneity, due to transitionary effects; while these properties could be imposed on long-run parameters.

1.4.2 Meta-analysis of Income Elasticity and Food Demand Projection

There are extensive empirical studies on food demand in China using a wide range of models and data sources during the past two decades. And then, we get a large number of demand elasticities with a large variance. Clarifying the determinants of heterogeneity in the estimated demand elasticities from the current literature is very critical for projecting food demand in the future and gauging the growth in food market. Therefore, a meta-analysis of income elasticity estimates is carried out in this dissertation.

A meta-analysis is a quantitative analysis of a body of similarly related primary studies (Card and Krueger, 1995). Meta-analysis provides a mean to analyze, estimate and discount the influence of the factors on the empirical results and further find out the determinants of the variation in primary results. In a meta-regression approach, estimated income elasticities are regressed on key characteristics of each study (Stanley and Doucouliagos, 2012), such as food category, region, data, publication status, model specifications, estimation method etc.

After controlling for the sample heterogeneity caused by factual factors, the meta-analysis usually suffers heteroskedasticity as demand elasticity estimates generally have heterogeneous variances due to different primary sample sizes and different estimation procedures studies (Smith and Kaoru, 1990; Nelson and Kennedy, 2009; Stanley and Doucouliagos, 2012; Tian and Yu, 2012). Estimates with smaller variances are more reliable and should be given greater weight in the meta-regression. However, variances are usually unavailable. Following other meta-analyses such as Nelson and Kennedy (2009), this dissertation employs weighted least squares (WLS), using sample sizes in primary studies as the weight, to deal with the heteroskedasticity as variances are often negatively correlated with the sample sizes.

The meta-analysis literature also indicates that the meta-regression model might not be linear (Walker *et al.*, 2008). This dissertation additionally adopts a Box-Cox model. Further projections of food demand in China were estimated based on the results of meta-regressions and assumptions on urbanization, population and economy growth. As the demand elasticity generally declines as income grows, this dissertation even provides the comparisons of two set of projections based on time-varying elasticities and constant elasticities respectively.

1.4.3 Calorie Consumption Transition and Finite Mixed Model

As previously mentioned, rapid economic growth is usually accompanied by the nutrition transition. Conventional wisdom tells that income growth can alleviate undernutrition and this is supported by many studies (Subramanian and Deaton, 1996; Abdulai and Aubert, 2004; Ogundari and Abdulai, 2013). The current literature also generally agrees that the relationship between increases in food expenditure and calorie intake is not linear. Consumers may show two different behavior patterns of food consumption with income growth (Jensen and Miller, 2010). When income is very low, consumers stay at the subsistent level, suffering from hunger and undernutrition, and their basic food need is often not secure, so that they tend to buy the calorie dense and cheap food such as cassava, wheat and rice which are also cheap sources of calories. This is often called "the Hunger Stage". Once they surpass the subsistent-level, calorie intake soon becomes saturate due to biological reasons. Consumers will pay more attention to the non-calorie attributes (such as good tastes, high quality, and diversity). This can be defined as "the Affluent Stage".

Calorie-income elasticity could be a good indicator to reveal the impact of further income growth on calorie consumption. Since calorie consumption patterns may vary across different consumer groups, which are mainly represented by income differences, consequently, income could be an important factor to explain the dynamics of calorie-income elasticities and one can generally expect that income elasticities of calorie consumption move downwards. Specifically, as people suffer from hunger, the marginal utility of additional calories is very high at the poor stage and calorie elasticities are relatively high. However, once the consumer passes the threshold of the subsistent level, and enters the affluent stage, the income elasticity decreases rapidly as the marginal utility of additional calories goes down significantly, and eventually becomes inactive with further income growth as consumers pay more attention to non-calorie attributes.

However, Jensen and Miller (2010) emphasize that the threshold level between the two stages is usually unobservable, and may be heterogeneous for different consumers. In addition, the definition of low or high-income group is relative and varies across countries, For instance, different countries often set different poverty lines to ensure minimum welfare (Chen and Ravallion, 2010). In addition, individual attitudes of nutrition in response to an income increase are unobserved in most cases. This mirrors the complexities of the relationships between nutrition intake and income growth. To capture the dynamics of calorie consumption, this dissertation proposes a finite mixture model (FMM). FMM could identify the structural changes in data as the sample is deemed as a mixture of populations rather than a single one in this approach (Everitt and Hand, 1981; Conway and Deb, 2005). Such a method has been applied in health economics literature, for instance when identifying the effectiveness of prenatal care (Conway and Deb, 2005). With an assumption of a mixture of the two behavioral patterns and probabilities, the FMM is adopted to identify the structural changes of the calorie elasticities in response to income gowth.

1.5 Empirical Studies

Economic growth would lead to substantial changes in food consumption followed by nutrition transition. To contribute the literature on the dynamic food demand and its consequences for nutrition transition, this dissertation carries out three case studies. The first two case studies carried out with Chinese data have strong policy implications not only for china but also for other emerging economies. As nutrition consumption usually adopted as an indicator of poverty, the third case study also illustrates important implications for poverty demolishing in developing countries.

1.5.1 Case Study I: Dynamic Food Demand in China

As previously mentioned, food demand dynamically changes as income grows due to the adjusting costs, such as habit formation, switching cost, and learning cost etc. The existence of adjusting costs implies that the static demand models in the current main stream literature might not correctly model consumer behaviors. Specifically, the income or expenditure elasticities estimated by these static models might be over-reported. It could lead to serious policy consequence if these elasticities are used for projection. In this study, a two-stage first order DLES-LA/DAIDS model is introduced and demand elasticities for 9 primary food products in urban China are estimated with the use of provincial aggregate data (1995-2010) from the China urban household surveys (UHS).

Consistent with the theoretical framework, this study evidences the existence of dynamic changes in food consumptions as significant short-run effects are statistically identified in the model. The results indicate that most of the primary food items, including grains, edible oils, meat, poultry and vegetables are necessities for urban households in China. In addition, the results indicate that all food items are price inelastic as the unconditional compensated own price elasticities are smaller than 1. The research also finds that the dynamic model tends to yield relatively smaller expenditure elasticities in magnitude than the static models do due to the friction effect of dynamic adjusting costs. However, the dynamic effects on own-price elasticities are inconclusive due to the add-up restriction.

1.5.2 Case Study II: Dynamic Food Consumption Projection

There is a large volume of empirical studies on food demand for China and projections for China's food demand. However, the projection results are significantly different. The income elasticities could be a major reason, as most projection models assume the elasticities are constant and estimated elasticities also vary widely in the current literature. In contrast, the second 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. The results indicate 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. And the meta-regression also indicates that the type of data (cross section, pooled, panel), income level, publication source, budgeting process, definition of income and demand model have significant impacts on the reported income elasticities in China after controlling for product differences. The urban-rural differences do not have a statistically significant impact on income elasticities for cereals after controlling for the differences in income between rural and urban areas.

Food projection has a prominent role in the food and agriculture policy making process, particularly in China. With the assumptions on urbanization rates projected by the DRC(China Development Research Center of the State Council), population growth rates indicated by the UN and per capita income growth rates of 6.6% per year from 2012 onward (OECD projection), the projections of income elasticities for those main food products for a few selected years are also worked out. The national-level income elasticities for general cereals and general meat were 0.40 and 0.48 respectively in 2000, and those elasticities slide to 0.12 and 0.36 in 2030.

Taking this into account, the projections based on constant income elasticities usually are higher than those time-varying projections except for wheat, which is lower. Furthermore, the differences between consumption projections based on time-varying income elasticities and values based on constant elasticities are substantial in quantities and increase over time. Specifically, the dynamic demand projection for cereal and meat will reach to 623.82 and 121.98 million tons respectively in 2030 in China, with the growth rate of 1.45% and 3.05% respectively in 2012-2030. The quantity differences between static and dynamic projections by 2030 are about 45.9 million tons for general cereals and 5.4 million tons for general meat.

1.5.3 Case Study III: Nutrition Transition with Economic Growth

As a consequence of rapid economic growth, many consumers change their consumption patterns. The changes of food consumption usually lead to a nutrition transition. The calories income elasticity would be one good indicator to illustrate the transition of nutrition consumption and the relationship between income and calories consumption is studied by many nutrition demand literature. The third study specifically sheds light on the relationship between calorie-income elasticity and income dynamics and proposes a finite mixture model (FMM) to model the behavioral transition of calorie consumption with an assumption that nutrition consumption is a mixture of behaviors in two stages: a poor stage and an affluent stage.

Based on 387 calorie-income elasticities collected from 90 primary studies, the results indicate that the calorie-income elasticity generally moves downwards as income grows, but the relationship between calorie-income elasticity and income varies across different stages. In the poor stage, the income elasticity declines rapidly. When income increases by 10%, the calorie income elasticity would decrease by 0.012. Once consumers reach the affluence stage, a further increase of income will have no significant impact on calorie-income elasticity, and it stays inactive.

Under the assumption in this research, two behaviors are mixed. When income increases, consumers tend to less likely exhibit the behavior indicative of the poor stage, and more likely behave as the ones in the affluent stage. The results identify the threshold income for calorie demand transition is 459.8 USD in 2012 prices (PPP). It implies that the transitional threshold for calorie consumption is 1.26 dollar/day, which is slightly lower than the World Bank poverty line (1.25 dollar/day in 2005 PPP prices). When income below this threshold value, calorie consumption is dominated by the poor stage behavior and people are suffering from undernutrition due to poverty.

2 Dynamic Food Demand in Urban China[1]

[1] This chapter was jointly written with Professor Xiaohua Yu and Professor Thomas Herzfeld

2.1 Introduction

The allocation of expenditure between goods and services is of continuing interest for researchers both from a theoretical and from an empirical perspective. Quite a few econometric models have been developed during the past decades, such as the Linear Expenditure System (LES) (Stone, 1954), the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980a), the Generalized Almost Ideal and Translog Demand Systems (GAITL) (Bollino and Violi, 1990), the Quadratic AIDS (Banks *et al.*, 1997), and the Quadratic Generalized Lewbel Demand Systems (QAITL) (Moro, 2003). These models are widely used in food demand analysis, particularly in emerging economies. The emerging countries are experiencing a rapid structural change in food consumption, which provide good case studies in a short period. Households tend to shift from traditional dietary dominated by staple food to high-value and quality food in company of rapid economic growth (Yu and Abler, 2009; Gao *et al.*, 1996). China is not an exception. After three decades of remarkable economic growth, the dietary structure changes dramatically in China and a large volume of literature has been devoted to this topic (e.g. Lewis and Andrews, 1989; Fan *et al.*, 1994; Fan *et al.*, 1995; Gao *et al.*, 1996; Ma *et al.*, 2004; Yen *et al.*, 2004; Wan, 2005; Jiang and Davis, 2007; Zheng and Henneberry, 2009; Abler, 2010).

However, most of the previous studies on food demand in China use static models. Deaton (1986) argues that static models, for the stake of simplicity, adopt a restrictive assumption that the food demand within one period only depends on the expenditure and prices in that period. With this assumption consumers are assumed to fully adjust to price and income changes instantaneously. However, many studies indicate that consumers do not simultaneously make the adjustment to income or price changes and get a balance in the transitionary process (Brown, 1952; Pollak, 1970; Kesavan *et al.*, 1993; Anderson and Blundell, 1983; Blundell, 1988; Yu and Abler, 2010). Actually, the demand for food may be a dynamic process due to the habit formation, switching costs, learning process etc. in the transition process (Nevo, 2010). Thus static models might lead to misspecifications of demand function and risk the accuracy and credibility of the estimated elasticities (Shukur, 2002). Some other studies illustrate that consumers dynamically adjust food consumption and the income elasticity changes as income grows. For instance, Blanciforti *et al.* (1986) suggest that the dynamic models are generally preferred over their static counterparts based on the U.S. consumption data from 1948-1978. With the use of static models, Zheng and Henneberry (2009; 2010; 2011) shed light on the impact of income changes on food demand and find that consumers change the consumption behavior as the demand elasticities vary across different income groups, in urban China. It implies the dynamic demand behavior. However, this static estimation of dynamic behavior is somehow contradictory. It confirms the methodological limitations of static demand models. There is a call for dynamic demand models.

To better understand the structural changes in food consumption in China with rapid income growth, this study attempts to make a step forward and proposes a complete two-stage dynamic demand model: a dynamic linear expenditure system (DLES) in the first stage to estimate the allocation of total expenditure between the food and other commodities and services, and a linear approximated dynamic almost ideal demand system (LA/DAIDS) model in the second stage to allocate food expenditure between different food items. With use of the data over 1995-2010 from China urban household surveys (UHS), an empirical evidence is provided.

The rest of this chapter is organized as follows. Section 2.2 presents a discussion of general forms of dynamic adjustments, followed by an introduction of the new two-stage DLES-LA/DAIDS model. Section 2.3 introduces the dataset used in this study and specifies an empirical two-stage DLES-LA/DAIDS model, followed by the results and discussions in section 2.4. Finally, the conclusions are presented in section 2.5.

2.2 Theoretical Framework

Generally, there are two main approaches to model the dynamic demand behavior. One is to take theory to play most of its role in the steady state solution such as habit persistence model, the other is vector time series specification that explicitly incorporates both the anticipated and unanticipated behavior (Blundell, 1988; Blanciforti *et al.*, 1986). The habit persistence model is more interpretive as it is derived directly from the economic theory, but the economic restrictions i.e., homogeneity, cannot be imposed sometimes as the direct involvement of lagged demand in Engel curve and the correspondent cost function is locally valid (Blanciforti *et al.*, 1986). The vector time series model is generated from a dynamic framework, which allows for a nonhomogeneous and nonsymmetrical short-run behavior and a homogeneous and symmetrical long-run behavior. There is evidence that time series model empirically tends to hold homogeneity and symmetry by data in general case (Anderson and Blundell, 1982; Anderson and Blundell, 1983; Marcus J, 1990). Thus, the present study adopts the vector time series approach to model the dynamic food demand.

A complete demand system is proposed empirically to plausibly replicate the consumption decision process with assumption of weakly separable utility. The utility tree approach, in which multi-stage budget occurs when consumers allocate their total expenditure in sequential stages, is usually used to circumvent the large number of variables in a complete demand model (Gorman, 1959b; Edgerton, 1997; Gorman, 1959a; Goldman and Uzawa, 1964; Deaton, 1986). Following this strategy, this study develops a two-stage dynamic complete demand system.

In a two-stage dynamic budgeting process, the broad group allocation depends on the prices and expenditure both in the past and current periods. Rational consumers need to maximize their total utility in the time horizon. The solution is given by the following maximization problem.

$$\begin{aligned} &\text{Max. } V = f\{v_1[B_1(L)E_1, C_1(L)p_1], \cdots, v_G[B_G(L)E_G, C_G(L)p_G]\}\ ,\ G \in N \\ &s.t. \ \ \sum_1^N E_{Gt}(u_{Gt}, p_{Gt}) = E_t \end{aligned} \tag{2-1}$$

where V is the total (indirect) utility. $B(L)$ and $C(L)$ are the lag polynomials. E and p denote expenditure and price, respectively. There are N groups of goods, and the indirect utility function for subgroup G is given by $v_G[B_G(L)E_G, C_G(L)p_G]$.

When the indirect utility for subgroup G is given, the expenditure allocation for a subgroup in the following second stage, becomes a problem of minimization of subgroup expenditure subject to a given utility level as follow,

$$\begin{aligned} &Min.\ E_G(u_G, p_G) = \sum_G D_G(L)p_k \cdot H_G(L)q_k, \quad k \in G \\ &s.t. \ \ u_G = v_G[B_G(L)E_G, C_G(L)p_G] \end{aligned} \tag{2-2}$$

where $D_G(L)$, and $H_G(L)$ are the lag operations for price and quantity respectively within subgroup G. For the stake of simplicity, it is very helpful to assume that there are no interrelations between expenditures and prices in different periods and prices are exogenous all over the time.

Theoretically, the prices over all time periods are needed for solving this multi-stage dynamic system. However, it is usually impracticable. To handle the price aggregation in a two-stage budgeting process, several useful approximations are available. Gorman (1959b) suggests using a strongly separable utility function, which implies the homothetic preferences for commodities in the same group (Fan *et al.*, 1995; Gao *et al.*, 1996; Edgerton, 1997; Deaton and Muellbauer, 1980b). Model selection should be based on two principles: theoretical consistence and easy practice. Doubtlessly, though linear expenditure system (LES) has very strict assumptions, it is still theoretically consistent. More importantly, LES does not require real price information in practice. Usually, for most non-food expenditures, price information unfortunately is not available in the survey Thus, many studies for two-stage models often combine a LES in the first stage, and a AIDS model in the second stage (e.g., Fan *et al.*, 1995)

Following the current literature, a dynamic linear expenditure system is chosen in the first stage to allocate the total expenditure, and a dynamic Almost Ideal Demand System is employed for the disaggregated subgroups of food in the second stage. Weak separability of its utility function is both a necessary and sufficient condition for estimating the second stage (Deaton and Muellbauer, 1980b).

On the basis of linear expenditure system (Stone, 1954), the dynamic demand function is the sum of the partial derivatives of the indirect utility function with respect to prices and expenditures up to the present with the use of Roy's identity.

$$A'(L)E_{gt} = B'(L)(E_t, p_t) + u_t \qquad \textbf{(2-3)}$$

The direct introduction of lagged demand leads to estimations of only short-run parameters (Bewley and Fiebig, 1990; Kesavan *et al.*, 1993). The standard estimators of the long-run responses involve ratios of regression coefficients, they typically do not possess finite sample moments and it is awkward to generate the asymptotic standard error (Bewley and Fiebig, 1990). To get an alternative convenient framework allowing for directly estimating short-run and long-run coefficients and their standard errors, we adopt Bewley's structural transformation and get the general DLES which can directly estimate both short-run and long-run coefficients and standard errors as follows (more details are provided in appendix A):

$$E_{gt} = C'(L)\Delta E_{gt} + \beta_g(E_t, p_t) + D'(L)\Delta(E_t, p_t) + v_t \qquad \textbf{(2-4)}$$

Where $C'(L)$ and $D'(L)$ are lag polynomials. v_t is the error term and Δ is difference operator. (E_t, p_t) is the vector of total expenditure and prices at time t.

On the basis of the price-independent generalized logarithmic (PIGLOG) expenditure function, similarly, we can get the general LA/DAIDS for the second stage as follows:

$$w_{it} = \kappa(L)\Delta w_{it} + \phi_i(p_t, E_t', P_t^*) + \omega(L)\Delta(p_t, E_t', P_t^*) + \mu_t \qquad \textbf{(2-5)}$$

where w_i is the budget share of food i within that group, $\kappa(L)$ and $\omega(L)$ are lag polynomials. (p_t, E_t', P_t^*) is the vector of price, group expenditure and Stone price index variables within that group, $logP_t^* = \sum_i w_{it} logp_{it}$. ϕ is the vector of steady-state condition parameters.

In dynamic demand systems, we could estimate both short-run and long-run elasticities. We have to point out that the short-run elasticities may not satisfy the demand properties, such as symmetry and homogeneity, due to transitionary effects; while these properties could be imposed on long-run parameters.

2.3 Dataset

The data used in this study is provincial aggregate data and it covers the urban households in 29 provinces (autonomous regions or municipalities) in China from 1995 to 2010[2]. The expenditure and consumption data come from the China Urban Household Surveys (UHS) conducted by the National Bureau of Statistics of China (NBSC) and implemented since the early 1980s (Wang *et al.*, 1995). UHS is a national uniform survey in China and sample households are selected by using a three-stage stratified sampling scheme (Cheng *et al.*, 1998). The total number of surveyed households increases from 35520 households in 1995 to 65607 households in 2010. NBSC publishes the provincial aggregate data based on these surveys annually in the China Urban Living and Price Yearbook. We assume that Hicks' composite commodity theorem holds for disaggregated goods within each subgroup. The assumption behind Hicks' theorem is strong (prices of a group of goods can only vary over time in strict proportion to each other), while Lewbel (1996) derives a generalized composite commodity theorem under which goods can be aggregated even if this assumption does not hold exactly. Then we could use the average prices of specific commodities in big cities within a province (usually the capitals), derived from China's Price Yearbook (various issues), as the

[2] Two provinces, Tibet and Chongqing, are excluded due to unavailable data.

proxies for the provincial prices.

Table 2-1 reports the income and the structure of expenditure. From 1995 to 2010, the national urban household disposable income has an average annual growth rate of 10.5%. The total expenditure consists of 8 broad groups, including food, clothes, household appliances and services, health care and medical services, transport and communication, recreation and education, residence, miscellaneous goods and services. The food expenditure annually grows at 6.9% for urban households over the same period, and it is obviously slower than the total expenditure growth rate. The food expenditure share declines from 49.9% in 1995 to 35.7% in 2010, which is consistent with the so-called Engel's law.

In order to take food-away-from-home (FAFH) into consideration, we divide total food expenditure into three groups: main food, FAFH, and other food[3], which are separable from each other in the first stage. There are 9 primary food categories in the main food subgroup: namely grains, edible oils, meat, poultry, eggs, fish, vegetables, fruits and dairy products[4]. The structure of the food expenditure at national level is presented in Table 2-2. It is clear that households allocate large shares of food budget on meat and vegetables. The food expenditure shares on these two subgroups are 14.39% and 10.44% respectively in 2010. Grains are also an important part, which accounts for 14.75% in 1995. However, the growth rate of expenditure on grains is only 2.65% over the period 1995-2010. Consequently, the expenditure share of grains decreases to 8.02% in 2010 for urban China.

[3] The main products of 'other food' group are tobacco and drinks. This group also includes starch, bean and bean-made product, seasoning, sugar and so on.

[4] Grains consist of rice and wheat; meat consists of pork (the dominant part), beef and mutton; poultry includes chicken and duck. Fish covers all kinds of fish and the other aquatic products, fruits include the dry fruits (but not important part), and milk and its product are included in the dairy products group.

Table 2-1 Per capita income and expenditure categories at national level in urban China (1995-2010, Yuan)

Year	Disposable Income	Total Consumption	Food	Clothing	Household Appliances and Services	Health Care and Medical services	Transport and Communications	Recreation, Education and Culture	Residence	Miscellaneous Goods and services
1995	4282.95	3537.57	1766.02	479.20	296.94	110.11	171.01	312.71	250.18	151.39
2000	6279.98	4998.00	1958.31	500.46	439.29	318.07	395.01	627.82	500.49	258.54
2005	10493.03	7942.88	2914.39	800.51	446.52	600.85	996.72	1097.46	808.66	277.75
2010	19109.44	13471.45	4804.71	1444.34	908.01	871.77	1983.70	1627.64	1332.14	499.15
1995		100.0%	49.9%	13.5%	8.4%	3.1%	4.8%	8.8%	7.1%	4.3%
2000		100.0%	39.2%	10.0%	8.8%	6.4%	7.9%	12.6%	10.0%	5.2%
2005		100.0%	36.7%	10.1%	5.6%	7.6%	12.5%	13.8%	10.2%	3.5%
2010		100.0%	35.7%	10.7%	6.7%	6.5%	14.7%	12.1%	9.9%	3.7%

Source: China Urban Living and China’s Price Yearbook (various issues)

Note: Disposable income and total consumption are measured in nominal terms.

Table 2-2 Structure of food consumption in urban household at the national level, 1995-2010

Year	Grains	Edible oils	Meat	Poultry	Eggs	Fish	Vegetables	Fruits	Dairy products	other food	FAFH
1995	14.75%	4.13%	17.36%	6.22%	3.94%	6.83%	10.75%	6.35%	1.78%	9.10%	18.80%
1996	14.26%	3.62%	16.96%	6.07%	4.13%	6.93%	10.85%	6.18%	1.92%	9.78%	19.30%
1997	12.26%	3.64%	17.42%	6.24%	3.79%	7.26%	10.50%	6.54%	2.13%	10.47%	19.76%
1998	11.77%	3.91%	16.48%	5.90%	3.48%	7.39%	10.22%	6.27%	2.49%	11.78%	20.31%
1999	11.15%	3.82%	15.57%	5.58%	3.39%	7.45%	10.07%	6.73%	2.91%	12.92%	20.42%
2000	9.63%	3.39%	15.46%	5.54%	2.89%	7.33%	9.82%	6.51%	3.50%	14.70%	21.22%
2001	9.34%	2.92%	15.12%	5.41%	2.82%	7.55%	9.65%	6.52%	3.98%	15.60%	21.09%
2002	8.38%	2.84%	14.75%	5.28%	2.60%	7.47%	9.40%	7.38%	4.61%	18.20%	19.08%
2003	8.03%	3.25%	14.58%	5.00%	2.52%	7.05%	9.78%	7.24%	5.16%	18.13%	19.26%
2004	8.81%	3.29%	14.87%	4.57%	2.52%	6.57%	9.47%	7.00%	4.89%	19.69%	18.33%
2005	8.31%	2.93%	14.64%	4.75%	2.45%	6.48%	9.45%	7.08%	4.76%	20.84%	18.32%
2006	7.92%	2.80%	13.37%	4.17%	2.17%	6.52%	9.59%	7.72%	4.83%	22.21%	18.71%
2007	7.67%	3.23%	14.41%	4.97%	2.31%	6.72%	9.61%	7.50%	4.43%	20.97%	18.16%
2008	7.71%	3.87%	15.99%	5.06%	2.15%	6.58%	9.61%	6.89%	4.46%	20.61%	17.08%
2009	7.46%	2.89%	14.59%	4.78%	2.07%	6.73%	9.97%	7.43%	4.38%	21.79%	17.90%
2010	8.02%	2.61%	14.39%	4.64%	2.04%	6.80%	10.44%	7.88%	4.13%	21.21%	17.83%

Source: China Urban Living and Price Yearbook (various issues)

Note: Grains consist of rice and wheat; meat consists of pork (the dominant part), beef and mutton; poultry includes chicken and duck. Fish covers all kinds of fish and the other aquatic products, fruits include the dry fruits (but not important part), and milk and its product are included in the dairy products group. The other food is the expenditure on food which is not covered by main food group and dining out. The dominant parts of the other food are tobacco and drinks.

2.4 Empirical Models

A parsimonious but data coherent dynamic empirical model is needed to be specified. In a general dynamic model, one shock spreads to future periods at a depreciating rate (Yu and Abler, 2010). Moreover, the inclusion of more lags considerably causes a decrease in degree of freedom. Given the limited length of time series data on food consumption in our research, it is necessary to reparameterize the general dynamic form to get a parsimonious model, which is the first order dynamic demand model. The first order DLES in the first stage is given by

$$E_{gt} = C_g' \Delta E_{gt} + \beta_g (E_t - \sum_{h=1}^{N} \gamma_h' p_{ht}) + \gamma_g' p_{gt} + D_g' \Delta(E_t, p_t) + v_t \quad \textbf{(2-6)}$$

Similar with the static demand models, economic restrictions such as adding-up, homogeneity and symmetry also can be tested in the dynamic model. As previously mentioned, the dynamic model allows for nonhomogeneous and nonsymmetrical short-run behavior due to the transitionary characteristics of consumer behavior in the short-run. The restrictions suggested by economic theory are only imposed on the long-run structure. Accordingly, the adding up constraint implies $\sum_g \beta_g = 1$ in first order DLES. The long-run expenditure elasticity and uncompensated price elasticities can be calculated as follows

DLES (long-run): $\eta_g = \beta_g E / E_g$ **(2-7)**

DLES (long-run): $e_{gh} = -\beta_g \gamma_h' p_h / E_g$ **(2-8)**

DLES (long-run): $e_{gg} = (1-\beta_g)\gamma_g' p_g / E_g - 1$ **(2-9)**

The subscripts t for the variables and elasticities are dropped for the simplification reason.

Similarly, the first order LA/DAIDS model for the second stage budgeting is yielded as follows

$$w_{it} = \kappa_i \Delta w_t + \phi_i + \sum_{j=1}^{s} \phi_{ij} logp_{jt} + \phi_{i0} log \frac{E_t'}{P_t^*} + \omega_i \Delta(p_t, E_t', P_t^*) + \mu_t \quad \textbf{(2-10)}$$

Where E_t' is the expenditure on a subgroup and i, j are the specific items within this subgroup. The adding up and homogeneity restrictions need to be imposed on the long-run effects, namely $\sum_{i=1}^{s}\phi_i = 1$, $\sum_{i=1}^{s}\phi_{i0} = \sum_{j=1}^{s}\phi_{ij} = 0$. Following the suggestion of Anderson and Blundell (1983), the symmetry restrictions are also imposed on the long-run parameters, namely $\phi_{ij} = \phi_{ji}, \forall_{i,j}$, leaving the short-run responses to be unrestricted. The long-run elasticity formulas are adopted from the approximations suggested by Green and Alston (1990); 1991). The conditional expenditure and uncompensated price elasticities in subgroup g are given as,

LA/AIDS (long-run) : $\eta_{gi} = 1 + \phi_{i0}/w_i$ **(2-11)**

LA/AIDS (long-run) : $e_{ij} = \left[\phi_{ij} - \phi_{i0}w_j\right]/w_i - \delta_{ij}$**,** **(2-12)**

where Kronecker delta $\delta_{ij} = 1$ when $i = j$, and 0 otherwise. The two-stage budgeting process implies relations between the sequential stages, such as the food expenditure has an impact on the grain consumption. Thus, in the two-stage dynamic demand model, it is plausible to take all the short-run and long-run effects in both stages into consideration when we estimate the unconditional income or price effect. However, the long-run effects should be the dominant part and the whole system approaches to a steady state condition. Once the systematic equations are estimated, we can calculate the approximate long-run unconditional demand elasticities. Following the instruction of Edgerton (1997), the total unconditional expenditure and uncompensated price elasticities are given by

$\eta'_{gi} = \eta_{gi}\eta_g$ **(2-13)**

$e'_{ij} = \delta_{gh}e_{ij} + \eta_{gi}w_{hj}(\delta_{gh} + e_{gh})$ **(2-14)**

It has long been recognized that demographic variables (such as the number of children and their ages) are the important determinants of consumer consumption patterns. However, the demographic information is not available in our aggregate dataset. In addition, we include regional dummy variables in estimation to capture regional differences (including demographical effect) and mitigate the effects of heteroskedasticity in food demand across different provinces in both stages.

An iterative Seemingly Unrelated Regressions (ITSUR) procedure is employed to estimate the DLES-LA/DAIDS model. The equation of 'other food' group is excluded due to adding up restrictions and the structure of data when we estimate the first order DLES in the first stage. The first order LA/DAIDS in the second stage is estimated with the homogeneity and symmetry restrictions with exclusion of dairy products to fulfill the adding-up constraint according to equation (2-10).

2.5 Empirical Results

All the estimated models are reasonable in terms of explanatory power. The results show that all estimated coefficients for short-run responses are statistically significant, indicating the presence of dynamic adjustments in demand behavior. The long-run expenditure elasticities and price elasticities are presented in Table 2-3 and Table 2-4.

Expenditure elasticities for main food, other food, clothing, household appliance and service and miscellaneous goods are all positive but less than 1, indicating they are necessities for the urban household in China. The long-run expenditure elasticity and the compensated own price elasticity for main food are 0.66 and -0.49 respectively. While the expenditure elasticities for FAFH, health care and medical service, transport and communication, recreation and residence are greater than 1, suggesting that they are luxury goods for urban households in China.

The rapid economic growth has led to an increasing urbanization and a rapid growth in the number of supermarkets, convenience stores and outlets (Gale and Huang, 2007). It changed food consumption patterns and motivated a significant rise in FAFH since 1980s (Dong and Hu, 2010). The long-run expenditure elasticity for FAFH is 1.39, much higher than the one for main food. The compensated own price elasticity for FAFH is price elastic with the value of -1.28.

Table 2-3 Long-run expenditure elasticities and price elasticities for broad commodity groups estimated by two-stage DLES-LA/DAIDS system

	main food	FAFH	other_food	clothing	houseapp	healthcare	transport	recreation	residence	miscellaneous
	long-run uncompensated price elasticities									
main food	-0.66	0.02	-0.03	-0.01	-0.01	0.01	0.05	0.01	0.00	0.00
FAFH	-0.14	-1.37	-0.06	-0.02	-0.01	0.03	0.10	0.01	0.01	0.00
other_food	-0.07	0.02	-0.41	-0.01	-0.01	0.01	0.05	0.01	0.00	0.00
clothing	-0.09	0.03	-0.04	-0.88	-0.01	0.02	0.07	0.01	0.01	0.00
houseapp	-0.07	0.02	-0.03	-0.01	-0.87	0.02	0.05	0.01	0.00	0.00
healthcare	-0.12	0.04	-0.06	-0.02	-0.01	-1.29	0.09	0.01	0.01	0.00
transport	-0.17	0.05	-0.08	-0.02	-0.02	0.03	-1.55	0.02	0.01	0.00
recreation	-0.10	0.03	-0.05	-0.01	-0.01	0.02	0.08	-1.07	0.01	0.00
residence	-0.11	0.03	-0.05	-0.02	-0.01	0.02	0.08	0.01	-1.06	0.00
miscellaneous	-0.09	0.03	-0.04	-0.01	-0.01	0.02	0.07	0.01	0.01	-0.98
	long-run compensated price elasticities									
main food	-0.49	0.06	0.02	0.06	0.04	0.05	0.11	0.09	0.07	0.03
FAFH	0.23	-1.28	0.05	0.14	0.08	0.12	0.23	0.18	0.14	0.06
other_food	0.11	0.06	-0.35	0.07	0.04	0.06	0.11	0.09	0.07	0.03
clothing	0.15	0.08	0.03	-0.78	0.06	0.08	0.15	0.12	0.09	0.04
houseapp	0.12	0.07	0.02	0.07	-0.82	0.06	0.12	0.10	0.08	0.03
healthcare	0.20	0.11	0.04	0.12	0.07	-1.21	0.21	0.16	0.13	0.05
transport	0.28	0.16	0.06	0.17	0.10	0.14	-1.39	0.22	0.17	0.07
recreation	0.17	0.10	0.03	0.10	0.06	0.09	0.18	-0.94	0.11	0.04
residence	0.18	0.10	0.04	0.11	0.07	0.09	0.19	0.15	-0.95	0.04
miscellaneous	0.15	0.08	0.03	0.09	0.05	0.08	0.15	0.12	0.09	-0.94
	long-run expenditure elasticities									
	0.66	1.39	0.68	0.92	0.74	1.24	1.70	1.05	1.11	0.90

Table 2-4 Estimated long-run expenditure elasticities and price elasticities for primary foods based on two-stage DLES-LA/DAIDS system

	grain	edible oils	meat	poultry	eggs	fish	vegetables	fruits	Dairy products
	conditional long-run uncompensated price elasticities								
grains	-0.66	0.02	0.11	0.07	0.16	0.14	0.05	0.02	-0.13
edible oils	-0.06	-0.40	0.13	0.12	-0.25	-0.06	-0.07	-0.22	-0.10
meat	-0.03	0.03	-0.82	-0.02	0.01	-0.05	0.03	0.00	0.01
poultry	0.04	0.09	-0.07	-0.98	0.00	-0.06	-0.06	0.19	-0.03
eggs	0.67	-0.25	0.28	0.08	-0.52	0.01	0.22	-0.20	-0.11
fish	0.06	-0.06	-0.24	-0.08	-0.06	-1.11	0.01	0.08	0.06
vegetables	-0.09	-0.04	-0.03	-0.05	0.00	0.03	-0.95	0.02	-0.02
fruits	-0.22	-0.15	-0.22	0.06	-0.16	0.03	-0.07	-1.04	0.03
dairy products	-0.72	-0.18	-0.37	-0.16	-0.20	-0.02	-0.28	-0.04	-0.61
	conditional long-run compensated price elasticities								
grains	-0.62	0.03	0.16	0.08	0.17	0.16	0.09	0.04	-0.11
edible oils	0.09	-0.35	0.34	0.18	-0.21	0.03	0.08	-0.12	-0.04
meat	0.11	0.08	-0.62	0.04	0.04	0.03	0.16	0.10	0.06
poultry	0.18	0.13	0.14	-0.91	0.04	0.03	0.07	0.29	0.03
eggs	0.64	-0.26	0.23	0.07	-0.53	0.00	0.19	-0.22	-0.12
fish	0.28	0.02	0.08	0.02	0.00	-0.99	0.23	0.23	0.14
vegetables	0.09	0.03	0.24	0.03	0.05	0.13	-0.77	0.15	0.05
fruits	0.06	-0.06	0.21	0.19	-0.09	0.19	0.21	-0.84	0.14
dairy products	-0.30	-0.04	0.25	0.03	-0.09	0.21	0.13	0.25	-0.45
	conditional long-run expenditure elasticities								
	0.23	0.90	0.84	0.88	-0.17	1.33	1.13	1.74	2.57
	unconditional long-run uncompensated price elasticities								
grains	-0.65	0.02	0.13	0.07	0.17	0.15	0.07	0.02	-0.12
edible oils	-0.01	-0.38	0.20	0.14	-0.23	-0.03	-0.02	-0.19	-0.08
meat	0.02	0.05	-0.75	0.00	0.02	-0.02	0.07	0.03	0.03
poultry	0.08	0.10	0.00	-0.95	0.01	-0.03	-0.02	0.23	-0.01
eggs	0.66	-0.25	0.26	0.08	-0.53	0.01	0.21	-0.21	-0.11
fish	0.14	-0.03	-0.13	-0.04	-0.04	-1.07	0.09	0.13	0.09
vegetables	-0.03	-0.01	0.06	-0.02	0.02	0.06	-0.89	0.06	0.00
fruits	-0.13	-0.12	-0.07	0.11	-0.14	0.08	0.02	-0.97	0.07
dairy products	-0.58	-0.13	-0.16	-0.09	-0.16	0.06	-0.14	0.06	-0.55
	unconditional long-run compensated price elasticities								
grains	-0.62	0.03	0.16	0.08	0.17	0.16	0.09	0.04	-0.11
edible oils	0.09	-0.35	0.34	0.18	-0.21	0.03	0.08	-0.12	-0.04
meat	0.11	0.08	-0.62	0.04	0.04	0.03	0.16	0.09	0.06
poultry	0.18	0.13	0.14	-0.91	0.04	0.03	0.07	0.29	0.03
eggs	0.64	-0.26	0.23	0.07	-0.53	0.00	0.19	-0.22	-0.12
fish	0.28	0.02	0.08	0.02	0.00	-0.99	0.23	0.23	0.14
vegetables	0.09	0.03	0.24	0.03	0.05	0.13	-0.77	0.15	0.05
fruits	0.06	-0.06	0.20	0.19	-0.09	0.19	0.21	-0.84	0.14
dairy products	-0.30	-0.04	0.25	0.03	-0.09	0.21	0.13	0.25	-0.45
	unconditional long-run expenditure elasticities								
	0.15	0.59	0.55	0.58	-0.11	0.88	0.74	1.14	1.69

In the second stage, most of the primary food items, including grains, edible oils, meat, poultry and vegetables are necessities for urban households in China. In addition, the results indicate that all food items are price inelastic as the unconditional compensated own price elasticities are smaller than 1. The long-run expenditure elasticity for grains is 0.15 and the compensated own price elasticity is -0.62. The estimated expenditure elasticity for edible oils is 0.59, while it has the lowest own price elasticity in magnitude (-0.35). When it comes to meat (including pork, beef, and mutton) the long-run expenditure elasticity and own price elasticity are 0.55 and -0.62 respectively.

The fish has a relatively higher long-run expenditure elasticity and the largest compensated own price elasticity in magnitude with the value of 0.88 and -0.99 (the scale of uncompensated own price elasticity is even larger than 1). It suggests that an increase in expenditure can significantly drive the consumption of fish (aquatic food) and the demand for fish is more sensitive to price changes than other kinds of food.

Fruits and dairy products, however, are luxury goods due to the long-run expenditure elasticities are 1.14 and 1.69 respectively, which suggests that the expenditure on both fruits and dairy products are expected to increase by larger amounts than that on grains, edible oils, meat, poultry and vegetables when household income keeps growing (Yu, 2012; Gao *et al.*, 2013). The own price elasticity for fruits is the second largest one in magnitude within the main food group with the value of -0.84. It indicates that the demand for fruits is quite price elastic.

Regarding eggs, the expenditure elasticity is, surprisingly, -0.11. It seems that egg is an inferior good for Chinese urban citizens. As we know, egg is an important source of protein in traditional Chinese diet, but it also contains lots of cholesterol. Medical sciences indicate that a high level of cholesterol is strongly associated with cardiovascular disease such as heart attack, stroke, and peripheral vascular disease. As income increases, Chinese consumers pay more attention to their health, and tend to substitute egg with other healthy protein sources such as fish and meat (Tian and Yu, 2012; Yu *et al.*, 2014).

2.6 Comparisons with Other Studies

To compare the differences between the results of two-stage DLES-LA/DAIDS and those from static demand models in a more intuitive way, Table 2-5 presents the comparison of estimated expenditure elasticities and own price elasticities from this study with those estimated by prevalent static models from the current literature for China in the past two decades.

In a static model where there is no adjusting cost (e.g. habit formation), any expenditure change will make the consumer instantaneously adjust his/her consumption to an optimal level (utility maximization). However, in a dynamic model, habit persistence will have some friction effect to reduce the adjustment of consumption. Consequently, the expenditure elasticities are smaller in dynamic models.

Phlips (1972) indicates that the income elasticities may be higher in the short run than in the long run due to the inventory adjustment with use of a dynamic linear expenditure model. Anderson and Blundell (1983) provide some evidence that the dynamic model yields smaller income elasticities for necessity goods possibly because of the adjustment in the short-run. The results of the study are consistent with those findings. In general, the expenditure elasticities from our study tend to be lower than those from static ones. For instance, the expenditure elasticity for grain in our study is 0.15, which is smaller than all mentioned studies except for Huang and Bouis (1996).

As mentioned above, without the assumption of simultaneously full adjustments in the static model, consumption behavior is confined by many factors, such as consumer expectation, habit formation, and learning/switching costs in the dynamic process and may not be able to adjust quickly with income changes. It would lead to a less sensitive response to the changes in income. Accordingly, income effect in the dynamic system would be smaller than that in the static model.

However, when it comes to own price elasticities, such an effect is less clear in the dynamic model (Table 2-5). Comparing with the current static models, no clear conclusions is found in the previous studies (e.g., Anderson and Blundell, 1983; Blanciforti *et al.*, 1986; Eakins and Gallagher, 2003). One possibility is that consumer can make very quick adjustments to price changes in the dynamic process. More importantly, the adjustment of consumption should satisfy the add-up restriction: Some larger price elasticities eventually must be offset by some smaller ones in a dynamic model.

Table 2-5 Comparison of results with earlier estimates from the literature on food demand in China

author	pub_time	journal	data_time	data_type	household	model	grains	edible oils	meat	poultry	eggs	fish	vegetables	fruits	dairy products
expenditure elasticity															
Our Study			1995-2010	panel	urban, China	DLES-LA/DAIDS	0.15	0.59	0.55	0.58	-0.11	0.88	0.74	1.14	1.69
Gould	2002	Agribusiness	1995-1997	pooled	urban, Jiangsu, Shandong, Guangdong	Translog	1.30			0.64	1.36	0.70	1.03	1.07	
Huang and Bouis	1996	IFPRI report	1991	cross section	urban, China	LA/AIDS	0.09	0.70	0.93				2.25	1.43	
Wu Li and Samuel	1995	AE	1990	cross section	urban, China	AIDS-AIDS	0.98[a]		1.17[b]		0.54	0.20	1.19	1.45	
Zheng and Henneberry	2009	RAE	2004	cross section	urban, Jiangsu	GAIDS	0.80	0.72	1.04	1.00	0.82	1.20	0.81	0.98	1.37
Zheng and Henneberry	2010	JAAE	2004	cross section	urban, Jiangsu	QUAIDS	0.72								
Fan el al.	1995	AJAE	1982-1990	Pooled	rural, China	LES-AIDS	0.50[a]		0.90				0.67		
Gao, Wailes and Cramer	1996	AJAE	1990	cross section	rural, Jiangsu	AIDS-GLES	0.52			0.29	0.91	0.89	1.26	0.72	
own price elasticity															
Our Study			1995-2010	panel	urban, China	DLES-LA/DAIDS	-0.62	-0.35	-0.62	-0.91	-0.53	-0.99	-0.77	-0.84	-0.45
Gould	2002	Agribusiness	1995-1997	pooled	urban, Jiangsu, Shandong, Guangdong	Translog	-0.91			-1.22	-1.15	-1.28	-1.38	-1.21	
Huang and Bouis	1996	IFPRI report	1991	cross section	urban, China	LA/AIDS	-0.43	-0.30	-0.28				-1.09	-0.87	
Wu Li and Samuel	1995	AE	1990	cross section	urban, China	AIDS-AIDS	-0.70[a]		-0.65[b]		-0.47	-1.40	-0.88	-1.14	
Zheng and Henneberry	2009	RAE	2004	cross section	urban, Jiangsu	GAIDS	-1.22	-1.31	-0.85	-0.35	-0.85	-0.10	-0.50	-0.87	-1.21
Zheng and Henneberry	2010	JAAE	2004	cross section	urban, Jiangsu	QUAIDS	-0.57								
Fan el al.	1995	AJAE	1982-1990	Pooled	rural, China	LES-AIDS	-0.63[a]		-0.31				-0.36		
Gao, Wailes and Cramer	1996	AJAE	1990	cross section	rural, Jiangsu	AIDS-GLES	-0.99			-0.53	-0.90	-0.81	-0.83	-0.96	

Note: [a] denotes the elasticity for rice. [b] The elasticity for pork which is the dominant part in meat group.

2.7 Conclusion

Consumers may not simultaneously adjust their behavior to changes in income in the short-run, confined by the adjusting costs, such as habit formation, switching cost, and learning cost etc. Existence of adjusting costs implies that the static demand models in the current main stream literature might not correctly model consumer behaviors. Specifically, the income or expenditure elasticities estimated by these static models might be over-reported. It could lead to serious policy consequence if these elasticities are used for projection. However, the results for own price elasticities might be inconclusive, because some larger price elasticities eventually must be offset by some smaller ones in a dynamic model possibly due to add-up restrictions.

This study develops a flexible two-stage dynamic model--a strongly separable DLES in the first stage and a LA/DAIDS with the inherence of weak separability in the second stage, to explain the dynamic food demand behavior in urban China. With use of provincial aggregate data on urban household consumption from 1995 to2010, we estimated the two-stage first order DLES-LA/DAIDS model.

We first empirically identified statistically significant short-run effects in our models. We then find that unconditional expenditure elasticities for food products are generally smaller than their counter-parts from the mainstream static models in the current literature. These evidence the existence of dynamic adjusting costs in food demand, consistent with the theoretical framework of this study. In addition, the results also indicate that most of the primary food products, including grains, edible oils, meat, poultry, fish and vegetables are necessities, and all primary foods are price inelastic in urban China. The research contributes to the demand analysis both empirically and methodologically, and can be used for better projections in policy simulation models.

3 Projecting Cereals and Meat Demand for China Based on a Meta-Analysis of Income Elasticities[5]

[5] This chapter was jointly written with Professor Xiaohua Yu, Professor David Abler, and Danhong Chen

3.1 Introduction

In conjunction with rapid economic growth for more than three decades, China is experiencing significant structural changes in food consumption (Yu and Abler, 2009). 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. Lewis and Andrews, 1989; Fan *et al.*, 1994; Fan *et al.*, 1995; Chern and Wang, 1994; Wu *et al.*, 1995; Gao *et al.*, 1996; Huang and Rozelle, 1998; Liu, 2003; Yen *et al.*, 2004; Gould and Villarreal, 2006; Jiang and Davis, 2007; Zheng and Henneberry, 2009; Abler, 2010). 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 high as 1.1 in a study by Han *et al.* (1997), much greater than the –0.37 estimated by Carter and Zhong (1999).

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 *et al.* (2004) 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 study 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 and Krueger, 1995). We use a meta-regression approach in which study results are regressed on key characteristics of each study (Stanley and Doucouliagos 2012). Similar to meta-analyses of the income elasticity of demand for cigarettes (Gallet and List, 2003), alcohol (Gallet, 2007), meat (Gallet, 2010a), calories (Ogundari and Abdulai, 2012) and Chinese total factor productivity (TFP) (Tian and 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 study 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 and Yu, 2013). 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? Second, after controlling for per capita income, is there a systematic difference in income elasticities between rural and urban households?

The remainder of this chapter is structured as follows: Section 3.2 introduces the data on income elasticities for cereals and meat demand in China; Section 3.3 describes the meta-regression models estimated in this study; Section 3.4 outlines the variables hypothesized to explain heterogeneities in income elasticity estimates; Section 3.5 presents the meta-regression results; Section 3.6 derives projections of income elasticities based on the meta-regression results and what these projections mean for future Chinese food demand; and Section 3.7 contains conclusions and policy implications.

3.2 Dataset

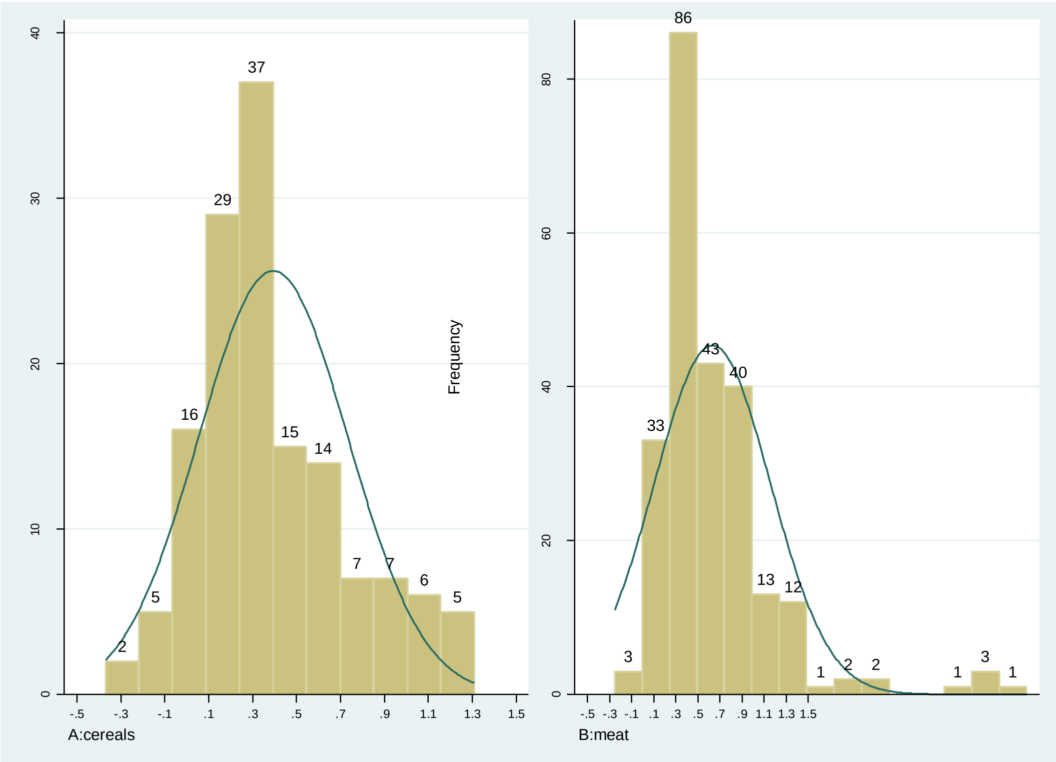
A meta-analysis first needs to compile a dataset which consists of the Meta variables of primary interest (income elasticity in this study) and the characteristics that may explain heterogeneities in the Meta variable. We conducted online keyword searches using Google, Google Scholar, AgEcon Search, 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 *et al.* (2008) pointed out that meta-analyses may suffer from selection bias due to the search criteria for primary studies. Given the focus of this study, 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 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 and 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 B. Figure 3-1 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.

Figure 3-1 Distribution of estimated income elasticities in the primary studies



3.3 Meta-Regression Models

Similar to other meta-analyses (Alston *et al.*, 2000; Gallet, 2007; 2010a; b; Tian and 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:

$$E_i = \alpha + X_i \beta + u_i \qquad \textbf{(3-1)}$$

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 (Smith and Kaoru, 1990; Nelson and Kennedy, 2009; Tian and Yu, 2012; Stanley and Doucouliagos, 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 study 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:

$$(E_i^{\theta} - 1) / \theta = \alpha + X_i \beta + u_i \qquad \textbf{(3-2)}$$

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 all meta-regression models using both the full samples and the restricted samples.

3.4 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 (Smith and Pattanayak, 2002; Nelson and Kennedy, 2009).

Table 3-1 provides a statistical description of those factors that are included in the meta-analyses. Table 3-2 presents definitions of the variables that are included in the econometric models.

Table 3-1 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

		Cereals			Meat		
		Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
	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

Note: the mean income elasticity is calculated from all estimations in each respective category.

Table 3-2 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

Variable	Definition
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

3.4.1 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 3-1 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 3-1 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.

3.4.2 Per Capita Income

Cross-country demand studies have found that income elasticities of demand for food items generally decline as per capita income increases (Seale and Regmi, 2006; Yu *et al.*, 2004). 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.

3.4.3 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 3-1 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.

3.4.4 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 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. Lewis and Andrews, 1989; Fan *et al.*, 1995; Wu *et al.*, 1995), while others use regional datasets (e.g. Gao *et al.*, 1996; Liu, 2003; Jiang and Davis, 2007; Zheng and Henneberry, 2009). Table 3-1 presents the regional differences in income elasticities for each food group. Generally, the mean values 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 (Ogundari and Abdulai, 2013; Gallet, 2010b). 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 and Henneberry, 2009). Panel data are often considered superior to cross-sectional data in controlling for unobservable heterogeneities in consumer choice (Yu and Abler, 2009).

3.4.5 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 3-1 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.

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 and 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 3-1 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.

3.4.6 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 (Walker *et al.*, 2008;

Tian and Yu, 2012; Stanley and Doucouliagos, 2012). 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 3-1 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.

3.5 Meta-Regression Results

The meta-regression results for cereals and meat products are reported in Tables 3-3 and 3-4, 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 meta-regressions.

Table 3-3 Meta-regression results for cereals

	Full Sample		Restricted Sample		
Explanatory Variable	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]

	Full Sample		Restricted Sample		
Explanatory Variable	OLS	WLS	OLS	WLS	Box-Cox
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]

	Full Sample		Restricted Sample		
Explanatory Variable	OLS	WLS	OLS	WLS	Box-Cox
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 R2	0.812	0.865	0.859	0.879	1.000
Sample Size	143	143	132	132	132

Notes: 1. Standard errors are provided in parentheses, while marginal effects for the Box-Cox model (evaluated at sample means) are provided in brackets.

2. Levels of significance: ***=1%, **=5%, *=10%.

3. The dependent variable in each regression is the income elasticity.

Table 3-4 Meta-regression results for meat products

	Full Sample		Restricted Sample		
Explanatory Variable	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*

	Full Sample		Restricted Sample		
Explanatory Variable	OLS	WLS	OLS	WLS	Box-Cox
	(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 R2	0.391	0.711	0.495	0.767	1.000
Sample Size	240	240	237	237	237

Notes: 1. Standard errors are provided in parentheses, while marginal effects for the Box-Cox model (evaluated at sample means) are provided in brackets.

2. Levels of significance: ***=1%, **=5%, *=10%.

3. The dependent variable in each regression is the income elasticity.

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 3-5 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.

Table 3-5 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

Note: a significant negative Z-statistic indicates that model 1 is rejected in favor of model 2

3.5.1 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 $\ln(2)\times0.142 \approx 0.10$ 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 *et al.*, 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 $\ln(2)\times0.221 \approx 0.15$ in the income elasticity for pork. Section 3.6 below contains projections of income elasticities at different income levels.

3.5.2 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 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 *et al.* (2012) 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. Their results may provide an explanation for our findings.

3.5.3 Results for Other Variables

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.

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.

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 *et al.*, 2004), then demand elasticities with respect to total income must be lower than elasticities with respect to total expenditure.

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.

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.

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.

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.

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.

3.6 Projecting Income Elasticities and Demands

Our results can be used to project income elasticities for China. Table 3-6 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 study was carried out 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 projection of 6.4% per year for 2011–2030 (Johansson *et al.*, 2012). 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).

Table 3-6 Estimated and projected income elasticities, 2000–2030

		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	13201	25014
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	19109	40961	77615
national	general cereals	0.403	0.266	0.174	0.119
	wheat	0.462	0.511	0.553	0.585

		2000	2010	2020	2030
	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	11590	29857	59731

Source: authors' calculations based on meta-regression results and assumptions described in text.

The figures in Table 3-6 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 3-1 and the meta-regression results in Table 3-3, the figures in Table 3-6 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 (Yu and Abler, 2009; Tian and Yu, 2013). 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 and 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 (DESA, 2013) 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.[6] 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

[6] 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.

changes in market-equilibrium quantities.

The results of this exercise for general cereals, rice, wheat, general meat, and pork are shown in Table 3-7. Pork is the predominant meat consumed in China, and specifically more than 60% of the meat consumed in China is pork (Yu and 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.

Table 3-7 Alternative food consumption levels for 2030 (million tons)

	Based on Constant 2010 Elasticities					Based on Time-Varying Elasticities				
year	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

Source: authors' calculations based on meta-regression results and assumptions described in text

3.7 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 be 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 meat than meals eaten at home (Bai *et al.*, 2012).

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.

4 Calorie Elasticities with Income Dynamics: Evidence from the Literature[7]

[7] This chapter was jointly written with Professor Xiaohua Yu

4.1 Introduction

Studies on nutrition demand have prominent implications in the policy making process, particularly for fighting undernutrition and poverty in developing countries. Poverty lines are set based on the nutrition requirement in many developing countries (e.g. rural China) (Chen and Ravallion, 2010). Most of economic development literature on nutrition demand focuses on the relationship between income and calories consumption: how income growth could help reduce undernutrition (Salois *et al.*, 2012; Tian and Yu, 2013). A large volume of literature has been devoted to this topic. Most of those studies shed light on estimations of calorie demand elasticity with respect to income and prices. Specifically, calorie-income elasticities draw much attention to the policy implications for demolishing undernutrition and improving the adequacy of energy intake, as they could reveal the impact of further income growth on calorie consumption. In addition, these elasticities could be used for projection of food demand in a region or a nation (in the long run), which provides information on the future food security.

Conventional wisdom tells that income growth can generally alleviate undernutrition and hunger particularly in developing countries. This is supported by many studies (Subramanian and Deaton, 1996; Abdulai and Aubert, 2004; Ogundari and Abdulai, 2013), even though metabolism could play an important role in hunger (Rolls *et al.,* 1998a; 1998b; 1999; 2000). The results in the current literature are quite heterogeneous. Estimated calorie-income elasticities range from near zero (e.g. Behrman and Wolfe, 1984; Behrman and Deolalikar, 1987; Behrman *et al.*, 1997; Bouis, 1994; Salois *et al.*, 2012etc.) to almost one (e.g. Pitt, 1983; Strauss, 1984; Behrman *et al.*, 1997etc.). Ogundari and Abdulai (2013) conducted a meta-analysis of 40 empirical nutrition demand studies to show a comprehensive review of the heterogeneity in calorie-income elasticities in the current literature. They find that publication sources and data structure are the main factors that could explain the heterogeneity of calorie elasticities. The linkage between income and calorie-income elasticities is not well scrutinized in the current literature (Ogundari and Abdulai, 2013) and there is still a debate on the dynamics of calorie consumption in connection to income growth.

As income grows, consumers tend to increase calorie consumption, but the marginal growth rate would decline when the calorie intake approaches the saturation point, as is predicted by the Engel's law. Consequently, one can generally expect that income elasticities of calorie consumption move downwards. This is supported by mounting evidence (Subramanian and Deaton, 1996; Skoufias, 2003; Yu and Abler, 2009; Skoufias *et al.*, 2011; Salois *et al.*, 2012; Jensen and Miller, 2010). Sahn (1988), using cross section data from 1980-1981, points out that income elasticities of calories range from 0.28 for high-income groups to 0.76 for low-income groups in Sri Lanka. Salois *et al.* (2012) shed light on the dynamics of calorie-income elasticities across countries over time and find that countries in higher quantiles have lower elasticities than those in lower quantiles. Skoufias *et al.* (2011) indicate that calorie-income elasticity gently declines as income increases and households that are above the median income spend additional earnings on buying higher quality food, rather than a pure increase in calories consumption. Tian and Yu (2013) find that for Chinese consumers with income below the moderate poverty line ($2/day) calorie-income elasticity is 0.32 and statistically significant, and when income is above the poverty line it decreases to 0.064 and becomes statistically insignificant. In general, these studies present the evidence that calorie consumption patterns may vary across different consumer groups, which are mainly represented by income differences. In other words, income could be an important factor to explain the dynamics of calorie-income elasticities. Unfortunately, this picture is not yet clear enough, even the latest survey on calorie-income elasticities by Ogundari and Abdulai (2013) does not pay much attention to this issue.

The current literature generally agrees that the relationship between increases in food expenditure and calorie intake is nonlinear. Jensen and Miller (2010) argue that consumers may show two different behavioral patterns of food consumption with income growth. When income is very low, consumers stay at the subsistent level, suffering from hunger and undernutrition due to a limited budget, and so they tend to buy the cheapest food, such as cassava, wheat and rice which are also cheap sources of calories (Jensen and Miller, 2011). This can be called the “Poor Stage”. Once they surpass the subsistent-level, calorie intake soon gets saturated due to biological reasons. Consumers pay more attention to non-calorie attributes, rather than merely pursuing additional calories, and the calories elasticity rapidly declines to a very low level and stays inactive. We define the second stage as the “Affluent Stage”. However, Jensen and Miller (2010) emphasize that the threshold level between the two stages is usually unobservable, and may be heterogeneous for different consumers.

Similarly, Logan (2006) also points out that the dietary substitution advocated by economists does not apply to nutrients, as food may be purchased for many reasons and consumption becomes diversified and shifts towards food with higher nutrient content when income increases (Deaton and Dreze, 2010; Yu *et al.*, 2014). The pattern of calorie consumption in response to income might be different across different income groups, particularly between the groups before and after surpassing the subsistent level. The low-income group who cannot afford to meet their caloric needs usually pays more attention to price and quantity issues, and mainly buys food products that are the cheapest available source of calories. However, when their income rises, consumers then have strong desires to improve other aspects of their meals (e.g., quality, taste, services) rather than to increase calories intake (Behrman and Deolalikar, 1987; Jensen and Miller, 2010; 2011). This implies that calorie intake would enter a stage of stasis, even though food expenditure still increases.

Low- or high-income group is a relative definition and varies across countries, and individual attitudes towards nutrition in response to an income increase are unobserved in most cases. Different countries often set different poverty lines to ensure minimum welfare, and some low income countries define their poverty lines by the minimum calorie intake or subsistent level calorie consumption (Chen and Ravallion, 2010; Jensen and Miller, 2010). However, the definition of subsistent level of calorie consumption is somewhat unclear (Jensen and Miller, 2010). This mirrors the complexities of the relationships between calorie intake and income growth. Hence, capturing the structural change in nutrition consumption and knowing the income threshold between poor and rich groups have important policy implications, as they are linked to poverty reduction policies. However, traditional methodologies do not shed much light on modeling the structural change in calorie consumption transition.

In order to fill the gap in the current literature, we propose a finite mixture model (FMM) to scrutinize the dynamics of calorie demand, since the FMM could identify structural changes in the data by assuming a mixture of different behavioral functions with mixing probabilities. In this study, we specifically assume that consumer behavior of calorie consumption is a mixture of two behaviors, that of the poor and that of the rich, and we assign a probability for each behavior. If the probability of the poor's behavior is higher than that of the rich, we define that this consumer stays at the poor stage; otherwise, this consumer enters in the affluent stage.

We collect income elasticities of calories consumption from the literature, as they could be a good parameter for measuring nutrition consumption behavior. Then we use the FMM to identify the structural changes of the elasticities in response to income change, with an assumption of a mixture of the two behavioral patterns. Such a method has been applied in health economics literature, for instance when identifying the effectiveness of prenatal care (Conway and Deb, 2005).

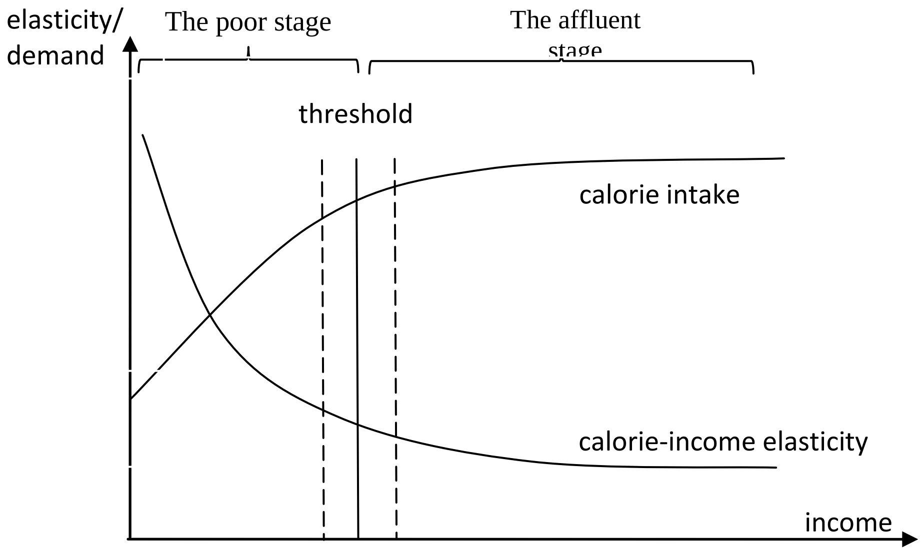
Section 4.2 will present the economic model with incorporation of the FMM; and Section 4.3 introduces the income elasticities of calorie consumption data collected from primary studies; and this is followed by a discussion of the results in Section 4.4; finally, this study is concluded in Section 5.5.

4.2 Empirical strategy

Common wisdom tells us that calorie consumption has a nonlinear relationship with income and it dynamically changes as income grows: calorie intake increases rapidly at the poor stage and then tends to become less sensitive at the affluent stage with increasing income, as it converges to a saturation point due to biological reasons(Tian and Yu, 2014). Jensen and Miller (2010) propose that consumers may show two different behavior patterns for food consumption along with income growth, specifically before and after surpassing the subsistent level. The low-income consumer group usually pays more attention to food price and nutrient quantity, as their basic needs for food consumption and nutrition requirements are not contented. As they suffer from hunger, the marginal utility of additional calories is very high at the poor stage. Thus calorie intake increases rapidly at the poor stage. Once they enter the affluent stage, calorie consumption converges to a saturation point due to biological reasons and consumers will switch to a strong preference for palatable and high quality foodstuffs, and then calorie intakes becomes less sensitive with increasing income (Behrman *et al.*, 1997; Behrman and Deolalikar, 1987; Subramanian and Deaton, 1996; Jensen and Miller, 2011; Yu *et al.*, 2014).

Correspondingly, as shown in Figure 4-1, with income growth, calorie elasticity with respect to income first declines rapidly and eventually stays at a very low level. Hence, calorie-income elasticities can be used for measuring the behavior of nutrition transition. When income is very low, the income elasticity for a consumer is relatively high. Consumers at the poor stage spend most of their additional income on food and calorie intake therefore grows rapidly with income. However, once the consumer passes the threshold of the subsistent level, and enters the affluent stage, the income elasticity decreases rapidly as the marginal utility of additional calories goes down significantly, and stays relatively low. The elasticity eventually becomes inactive with further income growth.

Figure 4-1 The changes in calorie consumption and calorie-income elasticity with income dynamics



However, the threshold level of calorie consumption between the two stages is usually unobservable and may be heterogeneous for different consumers (Jensen and Miller, 2010). The rich and the poor group are also relative definitions. It is very difficult to distinguish them simply by a cut-off number of per capital income as countries have different definitions of the poverty line (Chen and Ravallion, 2010), even though the World Bank set one poverty line at 1.25 $/day in terms of 2005 PPP (Purchasing Power Parity) price. For example, the absolute poverty line was $15.15/ day for the USA in 2010, while it was $0.55 for China and $1.0 for India. Therefore, the transition threshold usually lies more within a certain interval.

To illustrate the transitions of calorie consumption behavior explicitly, we simply assume there are two behavioral functions for calorie consumption in response to income changes, even though they are not explicitly observed. However, such an assumption will later be tested ex post with our data. The two behavior functions are defined as follows:

$$CE_{k,j} = g_k\left(Y_j, X_j\right) + \varepsilon_{k,j} \quad \textbf{(4-1)}$$

where $k = l,h$, respectively denote the poor stage and affluent stage for a consumer or a consumer group j. CE_j is the parameter for nutrition consumption behavior, specifically the calorie-income elasticity estimates collected from primary studies. Y_j and X_j respectively stand for the log real income and a vector of other observed factors (e.g., regional difference, data, nutrition survey, methods adopted in primary studies, etc.) explaining the heterogeneity of income elasticities. $g_k\left(\cdot,\bullet\right)$ is a behavioral function, and $\varepsilon_{k,j}$ is the error term following a normal distribution.

As aforementioned, the transition threshold and individual behavioral change are usually unobservable. However, it is clear that the calorie consumption transition is gradually taking place. We could reasonably assume that each observation of calorie demand estimations is a mix of two different behaviors: a poor-stage behavior and an affluent-stage behavior, and they respectively are assigned by a probability π_l and π_h, with $\pi_l + \pi_h = 1$. Thus, each observed calorie-income elasticity is expressed as

$$CE_j = \pi_l g_l\left(Y_j, X_j\right) + \pi_h g_h\left(Y_j, X_j\right) + \pi_l \varepsilon_{l,j} + \pi_h \varepsilon_{h,j} \quad \textbf{(4-2)}$$

One can speculate that π_h is positively correlated with income in the equation above. In contrast, π_l declines as income increases. As income increases, the probability that a consumer behaves in a way typical of the poor stage decreases. On the contrary, the probability of the affluence-stage behavior increases.

π_h or π_l could be a parameter modeling the behavioral transition of calorie consumption. When $\pi_h \le \pi_l$, the poor stage still dominates the calorie consumption behavior; and when $\pi_h \ge \pi_l$, the affluence stage starts to dominate. It is reasonable to define the threshold as $\pi_h = \pi_l = 0.5$ for behavioral change or nutrition transition.

Equation (4-2) is a typical finite mixture model (FMM) with two components. The sample is deemed as a mixture of populations rather than a single one (Everitt and Hand, 1981; Conway and Deb, 2005). The mixed probability density function (p.d.f.) in the FMM is

$$f(CE|Y,X,\theta)=\pi_l f(CE|Y,X,\theta_l)+\pi_h f(CE|Y,X,\theta_h) \quad \textbf{(4-3)}$$

f is the component density, which is assumed to be a normal density function, and then the model is a latent class regression. The parameter vector is $\varphi=(\pi,\theta')$, where π are mixing probabilities $\pi^T=\left(\pi_l,\pi_h\right)$, $\pi_k>0,\sum\pi_k=1$ and $\theta_k=(\beta_k',\sigma_k^2)'$. In order to estimate mixed probability density function, the model must assume a constant prior probability of a component group across all observations. Once we have the estimates of the two components, we could once again calculate the posterior probabilities of membership in each component for each observation with use of the Bayesian rule, conditional on all observed covariates and outcomes. The posterior probability that one observation belongs to class k is given by

$$P(k|CE,Y,X,\varphi)=\frac{\pi_k f(CE|Y,X,\theta_k)}{\sum\pi_k f(CE|Y,X,\theta_k)} \quad \textbf{(4-4)}$$

Thus, the posterior probability varies across observations and could be further used for examining the dynamics of calorie demand transition, and for identifying the calorie consumption behavior.

In this study, we assume there are two classes: the poor stage and the affluent stage. If $\pi_h\geq 0.5$, we categorize this sample in the affluent stage, otherwise in the poor stage. As aforementioned, the probability P_l that a consumer falls into the poor stage declines as income increases. Herein, it is plausible to assume the posterior probability follows a logistic growth curve

$$P_l=\frac{e^{Z\beta+e}}{1+e^{Z\beta+e}} \quad \textbf{(4-5)}$$

where Z is a vector of variables (including income) that could affect the probability of being poor P_l, and β is the corresponding parameter vector. e is the error term.

Rewriting Equation (4-5) yields an estimatable function,

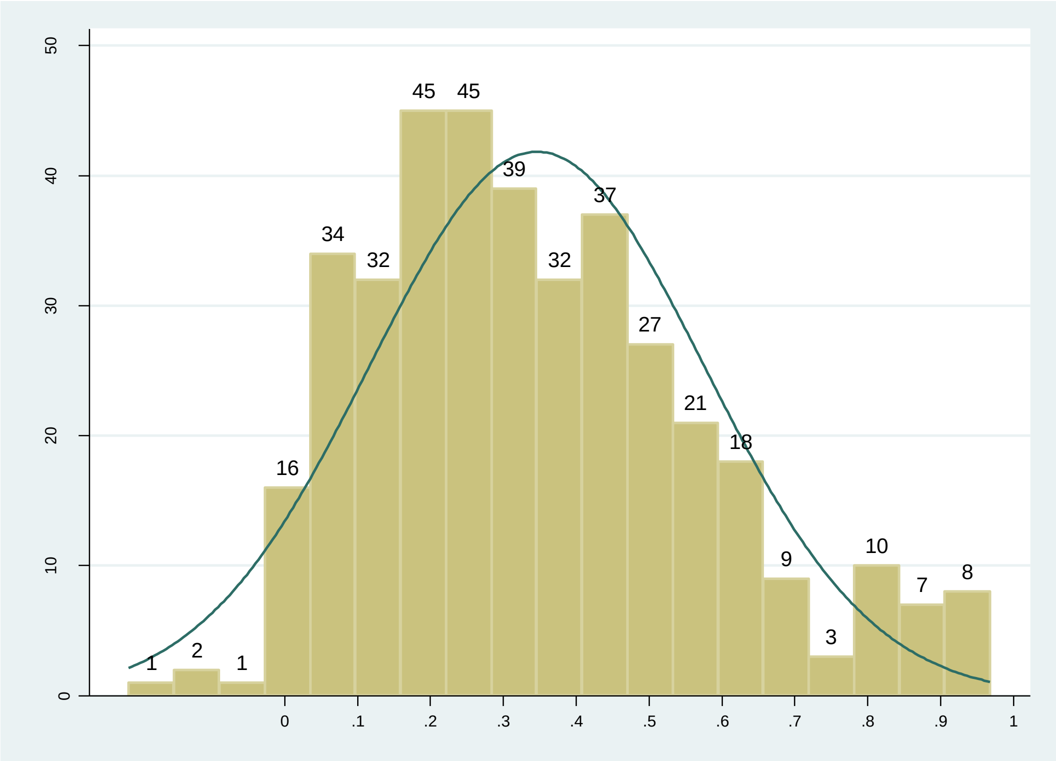
$$\ln\left(\frac{P_l}{1-P_l}\right) = Z\beta + e \tag{4-6}$$

After estimating Equation (4-6), we have the estimator $\hat{\beta}$ for β in hand. We can further scrutinize the dynamics of calorie consumption and illustrate the transition threshold. When we define the threshold at $P_l = 0.5$, that is $Z\hat{\beta}=0$, and we can solve for the level of threshold income.

4.3 Dataset

A large number of calorie elasticities have been estimated in the current literature and could be collected for serving the purpose of this study. We conducted online keyword (e.g. nutrition demand, calorie demand, and income elasticity) searches and endeavoured to collect as many primary studies as possible from different sources, such as AgEcon Search, Google, Google Scholar, Web of Science, and international institutions (e.g. International Food Policy Research Institute). We also checked the papers cited by or citing the available papers. Particularly, we carefully collected the citations in the comprehensive research by Ogundari and Abdulai (2013). The primary studies are published in various forms (i.e. research reports, books, journals, working papers) and the earliest research can be traced back to 1970s. Finally, a total of 90 studies are collected, which yield 387 estimated income elasticities of calorie consumption (intake). Figure 4-2 illustrates the distribution of the calorie-income elasticity estimates in our dataset. A summarized description of primary studies is also listed in the Appendix C.

Figure 4-2 The distribution of the estimated calorie-income elasticities in the primary studies



Note. There are 387 calorie-income elasticities in total, the average is 0.35 with a standard deviation of 0.23.

4.3.1 Heterogeneity Factors

Following the research of Ogundari and Abdulai (2013), variables that control for the study of specific attributes and that filter out the heterogeneities of the elasticities are also collected, specifically including the data structure, the location of the study, the nutrition survey used and the method adopted in the primary studies.

First, different from Ogundari and Abdulai (2013), this study will mainly shed light on the impact of income growth on income elasticity of calorie consumption, since the dynamics of their relationship is still debatable. However, "income" is differently defined in the current literature. Most studies use household expenditure, while some use actual income. Some evidence indicates that studies usually generate higher income elasticity of calorie consumption when they use expenditure as a proxy for income (Strauss and Thonas, 1990; Ogundari and Abdulai, 2013). However, for the sake of simplicity, we pool the income elasticity and expenditure elasticity of calorie consumption together. The difference is controlled in the Meta regression by using a dummy variable. Hereafter, we do not differentiate between income elasticity and total expenditure elasticity, and call both "income elasticity of calorie consumption".

Unfortunately, a few studies do not provide income or expenditure information. In this case, we use the GNP per capita in the reference year from the World Bank as a proxy. All income variables are measured by annual per capita income in local currency and are deflated to 2012 prices with the consumer price index (CPI) from that country. To better measure the living cost and income in different countries, we finally transform the income into international USD using the purchasing-power parity (PPP) exchange rates from World Bank.

Another issue is that different types of data are found to be associated with different estimation results in the literature (Gallet, 2010a; b; Ogundari and Abdulai, 2013). Though the current nutrition literature mainly uses cross-sectional data, time series and panel data are only adopted in a few studies. Cross-sectional data, which are generally individual observations, prevail in nutrition studies. In contrast, time series data is usually highly aggregated.

Second, the current nutrition literature covers many countries and most of which are developing countries in Asia or Africa. One can speculate that the nutrition elasticities could be different due to different dietary patterns and food structure for different countries, even though incomes are controlled in the analysis. We introduce region dummies (Asian countries, African countries and others) to control this heterogeneity.

Third, the reliability of reported calorie-income elasticities fundamentally depends on the accuracy of nutrition consumption reports (Bouis *et al.*, 1992). There are several methods used to measure nutrient consumption. Objective observer records have the advantage of being less subject to reporting biases, but they are time-consuming and costly (Dwyer, 1999). Most nutrition surveys follow subjective recall methods which rely on consumer's self-reported intakes over various spans of time, such as dietary recall[8] and food diaries, due to survey convenience and budget constraints (Dwyer, 1999; Thompson and Subar, 2008). However, nutrient consumption is subject to variations, such as seasonal, cyclical and longer range changes (Burk and Pao, 1976). Generally, random variation could be smoothed out along with loss of precision, when nutrient consumption data is collected over a longer recall period (Bouis, 1994). To distinguish the differences in the longitudinal dimension of the nutrition survey, we employ dummies for self-reported recall within 72 hours (e.g. the 24-hour, 48-hour or 72-hour dietary recall), less than 2 weeks (e.g. two-week food diary) and even longer (e.g. one month food diary survey, labeled here as "other survey method").

Another issue associated with the nutrition survey is whether the nutrients are actual intakes or just the quantities available (Bouis and Haddad, 1992; Bouis, 1994). There is evidence that income elasticity estimates based on calorie availability tend to be larger than those based on actual calorie intakes (Bouis and Haddad, 1992), since nutrition consumption derived from food expenditure surveys tend to be overestimated when richer households buy more food for guests, waste more, or give more food to pets. These factors should be controlled as well.

Fourth, direct and indirect approaches are common for the estimation of nutrient elasticities with respect to income (Huang, 1996). The direct approach simply estimates an Engel equation of the demand for calories. The indirect approach estimates a food demand system for a number of food groups and then converts the resulting food-income elasticities into calorie-income elasticities. The indirect approach typically estimates the demand systems at the aggregate level and tends to result in higher nutrient income elasticities than the direct estimates (Behrman and Deolalikar, 1987). Therefore, it is worthy to distinguish the two methodologies.

[8] In this approach, the respondent records the food products and beverages and the amounts of each consumed over one or more days.

In addition, the endogeneity problem, possibly resulting from simultaneity bias between income and calorie consumption, is observed in the literature and the instrument variable regression is proposed in many primary studies to correct it (e.g. Bouis and Haddad, 1992; Abdulai and Aubert, 2004; Ogundari and Abdulai, 2013 etc.). We also employ a dummy to control for this attribute of the primary studies.

Different econometric methods are also observed in the current literature due to advances in econometric techniques. The methods include ordinary least squares (OLS), maximum likelihood (ML) and a few other less commonly used methods (e.g. generalized method of moments), collectively labeled as "other estimation methods" in our analysis.

4.3.2 Descriptive statistics

Finally, the summary statistics of the abovementioned variables used in our study are presented in Table 4-1.

Table 4-1 Summary statistics of the calorie-income elasticities by study characteristics

	Variable	Definition	Obs	Mean
Pooled	elasticity	reported calorie-income elasticity	387	0.346
publication	working paper	Dummy for working/ discussion/ conference paper	104	0.372
	journal	Dummy for the study published in journal	218	0.336
	report	Dummy for the report or book chapter (reference)	65	0.339
Region	Asia	Dummy for the study was carried out in Asia	192	0.314
	Africa	Dummy for the study was carried out in Africa	90	0.422
	other regions	Dummy for the study was carried out in other region (reference)	105	0.340
Data	cross-section	Dummy for the use of cross-section data	202	0.389
	time series	Dummy for the use of time series data	17	0.208
	panel	Dummy for the use of other data (reference)	168	0.308
	income elasticity	Equal to 1 if the study used actual income	69	0.178
	expenditure elasticity	Equal to 1 if the study used expenditure as proxy for income (reference)	318	0.382
	calorie intakes	Equal to 1 if calorie is measured via the intake based on food consumption	132	0.277
	calorie available	Dummy for calorie is measured via the availability of food (reference)	255	0.382
	log real income	The log real income (base year 2012$)	387	7.265
Survey	survey_days	Dummy for the daily nutrition survey which covers less than 72	83	0.152

	Variable	Definition	Obs	Mean
		hours food recall		
	survey_week	Dummy for the weekly nutrition survey which covers less than 2 weeks food recall	113	0.381
	survey_other	Dummy for other nutrition survey (reference)	191	0.410
Method	direct method	Equal to 1 if the study used direct approach	330	0.302
	indirect method	Equal to 1 if the study used indirect approach (reference)	57	0.603
	ivregression	Equal to 1 if the study used instrumental variable regression	68	0.235
	ivregression0	Dummy for the study didn't use instrumental variable regression (reference)	319	0.370
	estimation_ols	Dummy for the use of OLS estimation	215	0.372
	estimation_ml	Dummy for the use of ML estimation	25	0.506
	estimation_other	Dummy for the use of other method (reference)	147	0.281

The average calorie-income elasticity for the 387 elasticity observations is 0.35 with a standard deviation of 0.23. This evidences a relatively large variation of calorie-income elasticities in the current literature. The majority of studies focus on Asia and Africa and the average calorie-income elasticities are 0.32 and 0.42 respectively. The number in African countries is slightly higher compared to Asia.

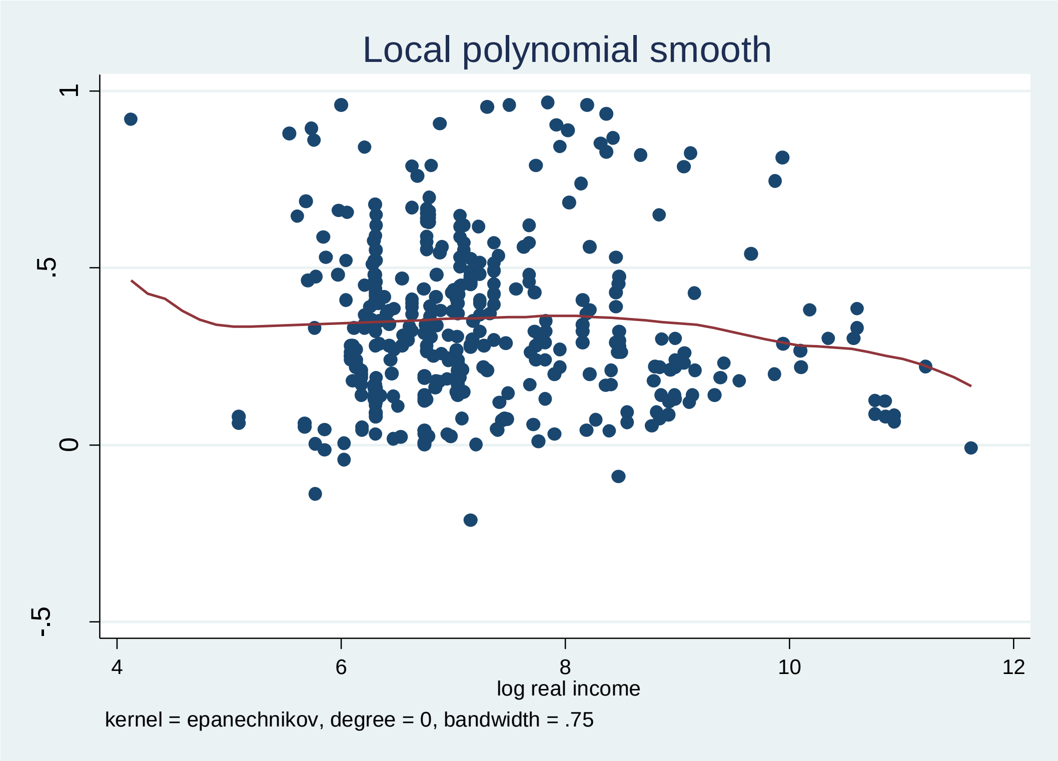
Consistent with Behrman and Deolalikar (1987), we find that calorie-income elasticities yielded from the indirect method are substantially higher than from the direct method, as the former and the latter are 0.60 and 0.30 respectively. The true calorie income elasticities (0.18) are generally lower than the expenditure elasticities (0.38), more precisely, the latter is almost double than the former. This is also consistent with the findings by Strauss and Thonas (1990) and Ogundari and Abdulai (2013).

4.4 Results and discussions

As aforementioned, the response of calorie consumption to income changes is nonlinear. Calorie intakes can eventually get to a saturate point as income grows and the calorie-income elasticity should gently decline along with income growth (Jensen and Miller, 2010).

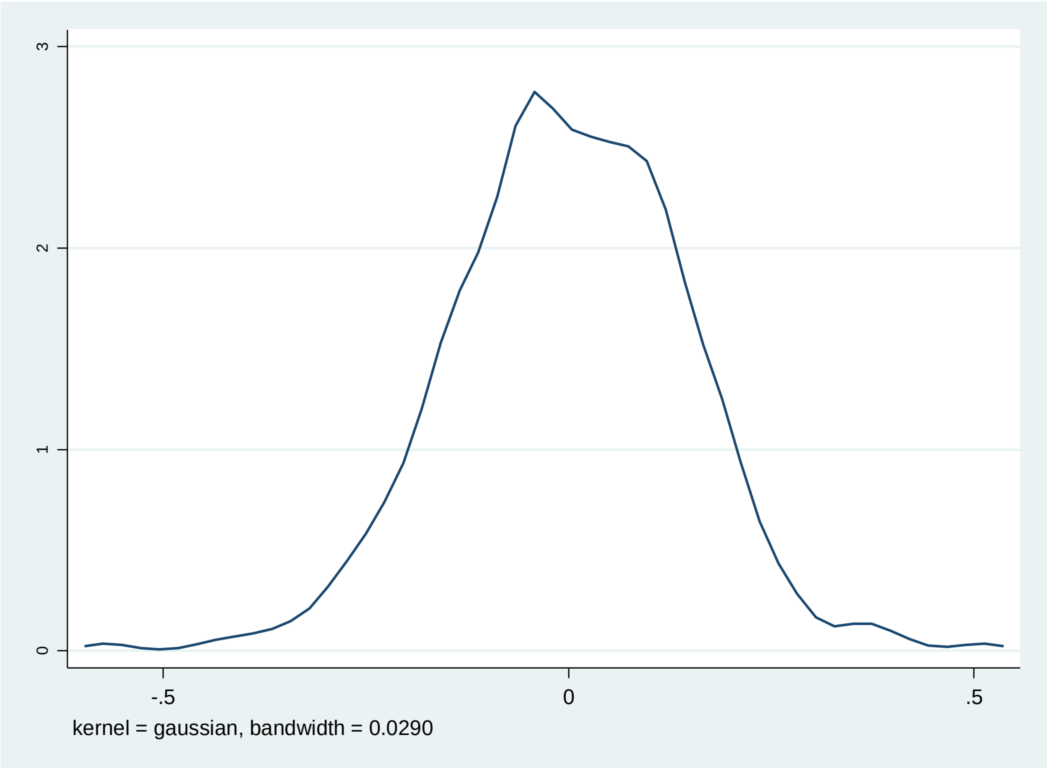
We first illustrate the relationship between calorie-income elasticity and log real income, with the use of a scatter plot. The result is presented in Figure 4-3. Consistent with the speculation, the result suggests that the calorie-income elasticity of calorie consumption declines as income grows. It seems that there is a structural change when other variables are not controlled. This evidences that the FMM is an appropriate approach to illustrate the complexity of the relationship between calorie-income elasticity and income.

Figure 4-3 The relationship between income and calorie-income elasticity



A straightforward way to check if the FMM is an appropriate model is to test the distribution of the residuals of the OLS regression. The distribution of the OLS residuals is depicted in Figure 4-4, which obviously shows that the error term is not normally distributed and evidences that there are at least two mixed components in the sample. The normality test on the residuals also rejects the null hypothesis of normal distribution at the significance level of 5%. The model selection criterions of both Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), indicate that the FMM with two latent components fits the data better than the OLS[9]. Therefore, consistent with our hypothesis, we observed two components in our sample.

Figure 4-4 Kernel density of OLS residuals from calorie-income elasticity regression



Note: The normality test on the residuals from OLS rejects the null hypothesis that the data is normally distributed (Prob =0.048)

The results are reported in Table 4-2, including the estimation results of an ordinary OLS regression and the FMM with two components, for the purpose of comparison. Clearly, there is a calorie demand transition with income growth. The two latent components are identified in proportions of 0.32 and 0.68 in the FMM model by the prior probability. Component 1 (or the poor stage) has a stronger response to income growth as the coefficient of log real income is -0.12, which is statistically significant at 1%. This implies that when log real income increases by 10%, the calorie-income elasticity would decrease by 0.012, given that other things remain constant. This implies that component 1 mainly consists of the low-income consumer group who usually pay more attention to the price and quantity of calories.

[9] We also tried the assumption of 3 components, but the model fails in converging.

Interestingly, when it comes to component 2, the coefficient of log real income is -0.023, which is a very small number and not statistically significant. This implies that the calorie intake becomes inactive as the real income surpasses the threshold of the poor stage. Component 2 mainly consists of the affluent group. Consumers in this group are generally close to the saturation point of calorie consumption and have a strong preference for palatable and high quality food products that are usually nutritious and expensive sources of calories.

Table 4-2 OLS and Finite mixture models for calorie-income elasticities

	OLS	FMM	
		component1	component2
working paper	0.063**	-0.337***	0.116***
	(0.03)	(0.10)	(0.03)
journal	0.098***	-0.131**	0.125***
	(0.02)	(0.06)	(0.03)
Asia	-0.095***	-0.347***	-0.095***
	(0.02)	(0.08)	(0.03)
Africa	0.070**	-0.098	0.038
	(0.03)	(0.07)	(0.04)
cross-section	0.011	0.088	-0.057**
	(0.02)	(0.06)	(0.03)
time series	-0.312***	0.109	-0.538***
	(0.05)	(0.11)	(0.09)
income elasticity	-0.105***	-0.332***	0.002
	(0.02)	(0.04)	(0.06)
calorie intakes	-0.022	0.028	0.007
	(0.02)	(0.05)	(0.04)
log real income	-0.032***	-0.121***	-0.023
	(0.01)	(0.03)	(0.01)
survey_days	-0.234***	-0.232***	-0.330***
	(0.02)	(0.06)	(0.05)
survey_week	-0.073***	-0.126***	-0.049**
	(0.02)	(0.04)	(0.02)
direct method	-0.282***	-0.056	-0.317***
	(0.02)	(0.06)	(0.03)
ivregression	-0.058**	-0.054	-0.046
	(0.03)	(0.05)	(0.04)
estimation_OLS	0.030	0.013	0.019
	(0.02)	(0.04)	(0.04)
estimation_ML	0.145***	-0.159*	0.297***
	(0.04)	(0.09)	(0.06)
intercept	0.867***	1.655***	0.864***
	(0.08)	(0.33)	(0.14)

	OLS	FMM	
		component1	component2
sigma		-2.304***	-2.329***
		(0.20)	(0.09)
p(normal)		0.32(0.06)	
N	387	387	
log likelihood	200.88	244.03	
AIC	-369.77	-418.06	
BIC	-270.62	-279.52	

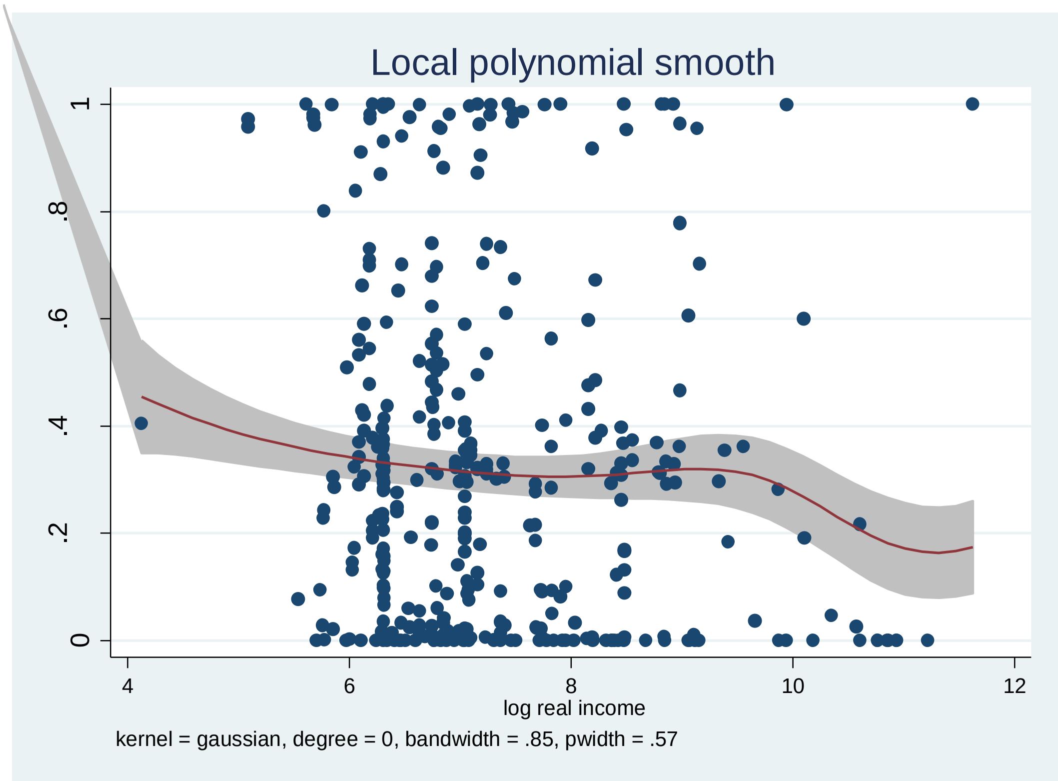
Note: standard errors are provided in parentheses. Levels of significance:***=1%, **=5%, and *=10%.

We could approximate the posterior probability of each component for each observation based on the estimation of Equation (4-2). Such posterior probabilities specifically decompose each sample into two components by assigning a probability. For instance, a posterior probability of 0.8 for component 1 implies that this observation is mixed by 80% of the poor stage and 20% of the affluent stage.

As we have the posterior probabilities at hand, we can further study the determinants of a posterior probability for each observation by regressing the posterior probability of component 1 on other factors. Figure 4-5 shows that the posterior probabilities of being component 1 and log real income are negatively correlated. The estimation results of Equation (4-6) for the posterior probability function are reported in Table 4-3. For the robustness check, we reported the results of three sets of independent variables. The coefficients for log real income are very close to each other and statistically significant in all three models, which evidences robustness of the results.

The coefficients for log income are negative and statistically significant at the 1% level. This indicates that the probability of belonging to the poor stage would decrease, or equally, the probability of belonging to the affluent stage would increase, when real income increases. As aforementioned, we define the threshold of nutrition transition as $P_l = 0.5$. Then by Equation (4-6), we could use the full model to predict the threshold income level of calorie demand transition with an assumption that other variables are at mean values.

Figure 4-5 The relationship between log real income and posterior probability of being component 1



The solution indicates that the real income equals 459.8$/year when we set the posterior probability $P_l = 0.5$ as the threshold, keeping other variables constant at mean values. This implies the income nutrition threshold is around 1.26 dollar/day in 2012 PPP prices. It is slightly lower than the 1.25 dollar/day poverty line (in 2005 PPP $) of the World Bank (Chen and Ravallion, 2010). This implies that consumers start to pass the subsistent level of food consumption and exhibit more affluent behavior even slightly below the World Bank poverty line. Nevertheless, such a finding provides an empirical foundation for the poverty line set by the World Bank.

In addition to income effects, there are several other notable findings. The signs of other coefficients indicate different sources of heterogeneity in the calorie-income elasticities. The results suggest an existence of publication bias (Tian and Yu, 2012); and that peer-reviewed journals report higher elasticities compared with articles in working/discussion papers. They are similar with the findings by Ogundari and Abdulai (2013), as the estimates for the regional effects reveal that calorie-income elasticity in Asia is generally lower than that in Africa, giving significant coefficients for those two variables.

Consistent with the evidence in other studies, our findings also indicate that calorie-income elasticities based on total expenditure as a proxy for income are significantly higher in magnitude than those conditional directly on income. It is feasible because the consumers smooth away the income shocks, while the impact of total expenditure would be more significant.

Consistent with the findings by Behrman and Deolalikar (1987), the coefficients for the direct approach in nutrition analysis, as well as those that employed the instrumental variable approach, are negative and significant. This implies that calorie-income elasticities derived from those methods tend to be lower in magnitude.

Finally, we find the nutrition survey methods also have significant impacts on calorie-income elasticity estimation. The nutrition surveys from a self-reported recall over a short span of time tend to yield more precise calorie consumption and lower calorie-income elasticity.

Table 4-3 Determinants of the posterior probability of being in component 1

	pos1(1)	pos1(2)	pos1(3)
log real income	-1.617***	-1.896***	-1.733***
	(0.28)	(0.34)	(0.34)
Asia		-1.357	-1.542
		(0.93)	(0.96)
Africa		-1.134	-1.447
		(1.07)	(1.13)
working paper			-1.631
			(1.02)
journal			0.348
			(0.92)
cross-section			-0.877
			(0.71)
time series			7.411***
			(2.05)
income elasticity			-2.662***
			(0.93)
calorie_intakes			0.583

	pos1(1)	pos1(2)	pos1(3)
			(0.84)
survey_days			-1.849*
			(0.99)
survey_week			-0.642
			(0.79)
direct method			3.686***
			(0.98)
Ivregression			-0.464
			(1.05)
estimation_OLS			-1.087
			(0.84)
estimation_ML			-7.262***
			(1.51)
Intercept	9.119***	12.087***	10.294***
	(2.03)	(2.91)	(3.19)
N	386	386	386
R-sq	0.082	0.087	0.223

Note: 1.Standard errors are provided in parentheses and levels of significance:***=1%, **=5% and *=10%.
2.The predicted real income value is 459.79 USD in 2012 dollars when we set the posterior probability threshold at 0.5 in the full model, keeping all other variables constant in the determinant regression.

4.5 Conclusions

The relationship between income and calorie consumption is one of the hotspots in nutrition studies, as it is strongly linked to policy implications. There is mounting literature devoted to this issue. Ogundari and Abdulai (2013) have addressed the existence of the heterogeneity in calorie-income elasticities. The current literature evidences that calorie income elasticities tend to decline when income grows, but the dynamics of calorie-income elasticity is still debatable. In order to fulfill the gap in the current literature, this study specifically sheds light on the relationship between income elasticity of calorie consumption and income dynamics, and uses a finite mixture model (FMM) to identity the transition of calorie consumption.

We collected 387 estimated calorie-income elasticities from 90 primary studies, which are used for the analysis in this study, as the calorie-income elasticities could reflect the behavior of calorie consumption. Following Jensen and Miller (2010), corresponding to different income levels, we assume that consumers may show two different behavioral patterns of food consumption along with income growth: a poor stage and an affluent stage. Methodologically, we assume that any observed calorie-income elasticity is a mixture of the two different behaviors with different probabilities. If we assign a probability to each component, it exactly comes to a FMM with two components.

With use of the FMM, our results by and large support our hypothesis that that the calorie-income elasticity generally moves downwards as income grows, but the relationship between calorie-income elasticity and income varies across different stages. In the poor stage, the income elasticity declines rapidly. Our results indicate that when income increases by 10%, the calorie income elasticity would decrease by 0.012. Once consumers reach the affluence stage, a further increase of income will have no significant impact on calorie-income elasticity, and it stays inactive.

The two behaviors are mixed. When income increases, consumers tend to less likely exhibit the behavior indicative of the poor stage, and more likely behave as the ones in the affluent stage. If we define the posterior probability of 50% in the FMM model as the income threshold for nutrition transition, the corresponding annual per capita income would be $459.8 (in 2012 PPP $), or equally 1.26 dollar/day, which is slightly lower than the poverty line proposed by the World Bank (1.25 dollar/day in 2005 PPP prices). Lower than this threshold value, calorie consumption is dominated by the poor stage behavior. They are suffering from undernutrition due to poverty. Even though this study implies that consumers start to pass the subsistent level of calorie consumption slightly below the World Bank poverty line, it nevertheless provides an empirical foundation for the poverty line set by the World Bank.

5 General Discussions

5.1 Contributions

Economic growth would lead to substantial changes in food demand. Specifically, the increasing income, urbanization and food supply modernization accompanied by economic growth have been largely reshaping the food consumption, especially in developing countries. Take China for example, the rapid income growth in past decades has led to substantial changes the food consumption patterns. And the diet of Chinese consumers is transforming towards high-value and high-quality products. The changes in food consumption are also associated with nutrition transition. Against this background, it is the purpose of this dissertation to contribute the literature on the dynamic food demand and its consequences for nutrition transition in three fields.

Firstly, according the introduction in Section 1.1, there is plenty of literature on the estimation of food demand and many models are developed for this purpose. However, the most used models in current literature are static models, in which the restrictive assumption of simultaneous adjustment to any changes in food consumption is adopted. While, consumers dynamically change food demand behavior with income growth and food consumption may be a dynamic process rather than a static one. Hence, consumers may not simultaneously adjust their behavior to changes in income in the short-run, due to adjusting costs, such as habit formation, switching cost, and learning cost etc.

One contribution of this dissertation is to propose a new food demand system to model the dynamic food demand process. With an adoption of transitionary demand process, this study developed a new approach of complete demand system with a two-stage dynamic budgeting system (DLES- LA/DAIDS): an additively separable dynamic linear expenditure system (DLES) in the first stage and a linear approximate dynamic almost ideal demand system (LA/DAIDS). And a two-stage first order DLES-LA/DAIDS model was estimated with the use of provincial aggregate data (1995-2010) from the China urban household surveys

(UHS). The research methodologically relaxes the restrictive assumption of instant adjustment in static models and allows consumers to make a dynamic decision in food consumption. Thus it pushes forward the techniques of demand analysis and can be used for better projections in policy simulation models. And it also can be employed with use of consumption data from other countries.

Secondly, despite the popularity of food demand estimation, the dynamics and heterogeneities in income elasticities are largely unrevealed. Given the large volume of income elasticities estimated by many researchers, it is a tough job to evaluate the elasticities and demand projections from those studies. This study provided a synthesis of existing research to scrutinize the heterogeneities and dynamics in current estimated demand elasticities and to evaluate a reasonable set of estimates for these elasticities. Moreover, this study presented a novel approach to work out the food consumption projections and projected the income elasticities and food consumption in the future in China based on a meta-analysis of income elasticities for main food (cereals and meat) and several assumptions.

Thirdly, as previously mentioned, nutrition transition is usually associated with the changes in food consumption patterns. There is plenty of literature to illustrate the linkage between income and calorie consumption and how income growth can help to demolish undernutrition. According the discussion in Section 1.3, people dynamically change their calorie consumption with income growth, however the calorie-income elasticities is not well scrutinized in current literature and there is still a debate on the dynamics of calorie consumption in connection to income growth. Another contribution of present dissertation is to fill this gap. This study employed the idea from Jensen and Miller (2010) and pushed it forwards with a hypothesis of mixed two-stage (a poor stage and an affluent stage) calorie consumption behaviors. It innovatively treated the calorie-income elasticities as mixed behaviors and adopted a finite mixture model (FMM) to model the behavioral transition of calorie consumption. The study empirically illustrated the dynamic relationship between calorie consumption transitions and income growth. It also gave a new approach to assess the poverty lines based on the threshold value of calorie consumption behavior in two stages.

5.2 General Conclusions from Empirical Studies

The three empirical studies generally deepen our understanding of dynamics in food demand and the consequences for nutrition transition with income growth. Specifically, this dissertation shows that food demand is one dynamic process and the responses of both food consumption and calorie consumption to income growth gradually change with economic development.

With respect to the dynamic food demand in China, the study showed that the rapid economic growth has led to substantial changes in food consumption and Chinese consumers substantially increased their consumption of meat, dairy products and fruits. With using the new dynamic demand system (DELS-AL/DAIDS), the results by and large support the hypothesis of the existence of dynamic changes in food consumptions as significant short-run effects were statistically identified in the model. The estimated elasticities also indicate that most of the primary food items, including grains, edible oils, meat, poultry and vegetables are necessities for China urban households, and all the food items are price inelastic. Finally, there is a difference between the results from the dynamic model and static versions. The dynamic model tends to yield relatively smaller expenditure elasticities in magnitude than the static models do due to the friction effect of dynamic adjusting costs.

When it comes to the dynamics in income elasticities and food consumption projections, the results show that income elasticity generally tends to decline when per capita income increases with the exception of wheat, which increases. However, the changes of income elasticity with income growth vary for different products. The income elasticity for pork declines faster with income growth than the elasticity for meat group as a whole. It has been estimated that a doubling of per capita income would lead to declines of about 0.15 and 0.10 in the income elasticity for pork and wheat respectively. The meta-regressions also indicate that the factors, including type of data (cross section, pooled, panel), publication source, budgeting process, definition of income and demand model, have significant impacts on the reported income elasticities in China. However, the urban-rural differences do not have a statistically significant impact on income elasticities for cereals after controlling for the differences in income between rural and urban areas.

With the assumptions on urbanization rates, population growth rates and per capita income growth rates, the projected income elasticities for main food products indicate that income elasticities for general cereals and general meat were 0.40 and 0.48 respectively in 2000, and those elasticities slide to 0.12 and 0.36 in 2030. Taking this into account, the projections based on constant income elasticities usually are higher than those time-varying projections except for wheat and the divergences increase over time. Specifically, the dynamically projected demand for cereal and meat will reach to 623.82 and 121.98 million tons respectively in 2030 in China. The quantity differences between static and dynamic projections by 2030 are very big, about 45.9 million tons for general cereals and 5.4 million tons for general meat.

In the context of nutrition transition with income growth, the results largely support the hypothesis that the calorie-income elasticity generally moves downwards as income grows, but the relationship between calorie-income elasticity and income varies across different stages. In the poor stage, income is very low and the marginal utility of calorie is relatively high. Consumers have strong desire to pursue more calorie intakes, and calorie-income elasticity therefore is relatively high in the poor stage. According to the empirical study, calorie-income elasticity declines rapidly as income grows in poor stage and consumers shift towards non-calorie attributes. When income increases by 10%, the calorie-income elasticity would decrease by 0.012. Once consumers reach the affluent stage, food choice becomes more complicated and a further increase of income will have no significant impact on calorie-income elasticity. Given the two mixed behaviors in two stages, consumers tend to less likely exhibit the behavior indicative of the poor stage, and more likely behave as the ones in the affluent stage when income grows. The threshold income for calorie demand transition is 459.8 USD in 2012 prices (PPP), namely 1.26 dollar/day, which is slightly lower than the World Bank poverty line (1.25 dollar/day in 2005 PPP prices). When income below this threshold value, calorie consumption is dominated by the poor stage behavior and people are suffering from undernutrition due to poverty.

5.3 Policy Implications

Food demand and nutrition transition analyses have prominent policy implications as they are the foundations of demand projections and undernutrition demolishing. Food consumption patterns dynamically change with economic growth which would further lead to nutrition transition. Hence, it is of great importance to deepen our understanding of dynamics in food demand and nutrition transition with a view to agricultural and food policies. This dissertation has contributed new insights regarding those issues. Based on these new insights with respect to dynamic food demand modeling and the dynamics of income elasticities and calorie consumption transition, conclusions regarding agricultural and development policies can be deduced.

Consistent with conclusions form literature on dynamic food demand, the study on dynamic food demand in urban China gave evidence that the food consumption is a dynamic process rather than a static one. Neglecting this fact would undermine the accuracy and credibility of estimations in food demand analysis. Therefore, the existing demand models are not well suited to capture demand dynamics. In the dynamic model, the assumption of simultaneously full adjustments, which is adopted in static models, is abolished. The results from different kinds of modelling vary from each other. Actually, the results indicate that the dynamic model tends to yield relatively smaller expenditure elasticities in magnitude than the static models do. And the traditional expectation of food demand growth is generally overestimated as most primary food products are estimated to be necessity goods for China urban households in present dissertation. When policy makers work on food demand analyses and agricultural policies, it is wisdom to take the transitionary demand behavior into account and to adopt dynamic models, especially in China as high-value products are increasingly substituting for staple food.

The case studies also illustrate that, when consumers dynamically adjust food consumption, the income elasticity changes as income grows. For instance, the projected income elasticity for general cereals declines from 0.40 to 0.12 in 2000-2030. It implies there would be a divergence in income elasticities when policy makers work out demand projections in both static and dynamic ways. Taking this into consideration, the projections based on constant income elasticities usually are higher than those time-varying projections and the divergences increase over time. As previously presented in the dissertation, the consumption of cereal and meat grows at the speed of 1.45% and 3.05% respectively in 2012-2030. While the growth rate is even higher when one uses static income elasticities. This largely evidences that the dynamics of income elasticity would be an important factor for projecting food consumption, especially when consumers are experiencing substantial economic growth in the case of China. Given the tight domestic supply of food products in China, incorrect projection could lead to inappropriate trade policy, which eventually distorts the world food market. Therefore, models used to make long-term demand projections should incorporate the dynamics of income elasticities. The first two case studies not only have strong policy implications for China but also for other emerging economies.

As poverty lines are set based on the nutrition requirement in many developing countries, the third case study on calorie demand transition has prominent implications for fighting undernutrition and poverty. As the relationship between increases in food expenditure and calorie intake is nonlinear, consumers may show two different behavior patterns of calorie consumption with different income levels. With adoption of a finite mixture model (FMM) to identify the transition of calorie consumption, the way to estimate the threshold income of different behaviors in poor stage and affluent stage provides a novel approach to measure the poverty threshold. Policy makers could adopt those revealed preferences and FMM to measure the poverty. It also provides a strong empirical support for the poverty line set by the World Bank.

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Appendix

A: Bewley's Structural Transformation

Given a vector time series approach, a general dynamic linear model can be written as follow

$$A(L)Q_t = B(L)x_t + u_t$$

where $A(L)$ and $B(L)$ are lag polynomials, $A(L) = I - A_1L - A_2L^2 \cdots - A_pL^p$ and $B(L) = B_0 + B_1L + B_2L^2 \cdots + B_qL^q$. Q_t is a vector of demand at the period t, which depends upon the non-stochastic expenditure and price variables x_t. u_t is the error term. With the Bewley transformation structural model (Bewley, 1979), the general dynamic linear model can be rewritten as follows

$$Q_t = C(L)\Delta Q_t + \Omega x_t + D(L)\Delta x_t + v_t$$

where $C(L) = 1 + C_1L + C_2L^2 \cdots + C_{p-1}L^{p-1}, C_i = -\sum_{j=i+1}^{p} A_j / A$,

$$D(L) = D_0 + D_1L + D_2L^2 \cdots + D_{p-1}L^{p-1},\ D_i = -\sum_{j=i+1}^{q} B_j / A,$$

$$\Omega = \sum_{j=0}^{q} B_j / A, v_t = A^{-1}u_t.$$

where Δ is the difference operator. This general dynamic model directly identifies the long-run steady state condition parameters along with the short-run dynamics, and long-run multiplier matrix Ω is estimated with a standard error.

B: List of Primary Studies on Food Demand in China

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 el 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

Authors	Where Published or Released	Publication/ Release Date	Rural or Urban	Data	Product Category	Mean Income Elasticity
					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 qion	Chinese	2010	rural	cross-section	meat	0.752
			urban	cross-section	meat	0.249
Chang Xaingyang, Li Aiping	Chinese	2006	rural	cross-section	cereals	0.072
Li Dongsheng	Chinese	1995	rural	cross-section	cereals	0.216
Li Dongsheng, Yang yiqun	Chinese	2001	rural	cross-section	cereals	0.166
					meat	0.300
			urban	cross-section	cereals	0.133
					meat	0.438
Liu hua, Zhong funing	Chinese	2009	urban	cross-section	cereals	0.294
					meat	0.376
Liu Zhongxia	Chinese	2010	urban	cross-section	meat	0.386
Mu yueying	Chinese	2001	rural	panel	cereals	0.658
					meat	1.352
			urban	panel	cereals	0.606
					meat	1.294
Qu Xiaobo, Huo Xuexi	Chinese	2007	rural	cross-section	cereals	0.872
					meat	1.141
Zhang minghong et al.	Chinese	2004	rural	cross-section	cereals	0.070
					meat	0.250
Zheng and Henneberry	RAE	2009	urban	cross-	cereals	0.795

Authors	Where Published or Released	Publication/ Release Date	Rural or Urban	Data	Product Category	Mean Income Elasticity
				section		
					meat	1.021
Zheng and Henneberry	Agribusiness	2011	urban	cross-section	cereals	0.118
					meat	0.238

Note: 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).

C: Summary Statistics of the Primary Studies on Calories Demand

Author	p_time	Journal	Country	elasticity
Abdulai and Aubert	2004	Food Policy. vol.29:113-129	Tanzania	0.52
Abudulai and Aubert	2002	working paper Swiss Federal Institute of Technology, Zurich	Tanzania	0.57
Abudulai and Aubert	2004	Agricultural Economics vol.31:67-79	Tanzania	0.43
Alderman and Higgins	1992	working paper. Cornell Food and Nutrition Policy Program	Ghana	0.51
Alderman etc.	1988	report No.4 International Food Policy Research Institute	Pakistan	0.39
Alderman	1987	report No.64 International Food Policy Research Institute	India	0.42
Al-mulhim	1991	Agricultural Science vol.3:179-188	Saudi Arabia	0.24
Aromolaran	2004	Food Policy vol.29:507-530	Nigeria	0.18
Aromolaran	2004	working paper. Economic Growth Center, Yale University	Nigeria	0.08
Ayalew	2000	working paper. Faculty of Economics, Katholieke University	Ethiopia	0.14
Babatunde	2008	working paper. Department of Agricultural Economics and Social Sciences, University of Hohenheim	Nigeria	0.16
Babatunde etc.	2010	Agricultural Science vol.2-2:135-146	Nigeria	0.18
Basu and Basole	2012	working paper. Political Economy Research Institute, University of Massachusetts	India	0.33
Beatty and LaFrance	2005	American Journal of Agricultural Economics vol.87(5):1159-1166	United States	0.21
Behrman and Wolfe	1984	Journal of Development Economics vol.14:105-128	India	0.06
Bouis and Haddad	1992	Journal of development economics vol.39:333-364	Philippines	0.28
Bouis etc.	1992	Food Policy vol.17(5):349-360	Kenya	0.27
			Philippines	0.31
Bouis	1994	Journal of development economics vol.44:199-116	Kenya	0.25
			Philippines	0.33
Braun etc.	1989	report, No.73 International Food Policy Research Institute	Guatemala	0.31
Braun etc.	1991	report, No.85 International Food Policy Research Institute	Rwanda	0.48
Chernichovsky and Meesook	1987	report, No.670 World Bank	Indonesia	0.45
Dawson and Tiffin	1998	American Journal of Agricultural Economics vol.80:474-481	India	0.34
Dawson	2002	Pakistan journal of Nutrition. vol.1(1):64-66	Pakistan	0.19
Dimova etc.	2012	working paper. Brooks World Poverty Institute, University of Manchester	Bulgaria	0.78
Djebbari	2005	working paper. Institute for the Study of Labor (IZA), Bonn	Mexico	0.29
Ecker etc.	2010	The African Journal of Agricultural and Resource Economics vol.4(2):175-194	Rwanda	0.65
			Tanzania	0.59
			Uganda	0.68
Ecker and Qaim	2010	world development vol.39(3):412-428	Malawi	0.77
Edirisinghe	1987	report No.58 International Food Policy Research	Sri Lanka	0.42

Author	p_time	Journal	Country	elasticity
		Institute		
Gaiha etc.	2010	working paper (2010/16) Australia South Asia Research Centre (ASARC)	India	0.34
Gaiha etc.	2010	working paper (2010/15) Australia South Asia Research Centre (ASARC)	India	0.08
Gaiha etc.	2012	working paper. Research Institute for Economics and Business Administration (RIEB), Kobe University	India	0.33
Garcia and Pinstrup-Andersen	1987	report No.61 International Food Policy Research Institute	Philippines	0.33
Gawn etc.	1993	Applied Economics vol.25(6): 811-830	United States	0.27
Gerbens-Leenes etc.	2010	Appetite vol.55(3):1-12	France and Britain	0.23
			south Europe	0.21
			57 countries	0.14
Gibson and Kim	2013	Economics letters vol.118:23-25	Papua new guinea	0.22
Gibson	2000	working paper. University of Waikato	Papua new guinea	0.37
Gibson and Rozelle	2010	the Journal of Development Studies vol.38(6):23-46	Papua new guinea	0.41
Greer and Thorbecke	1986	Journal of development economics vol.24:59-74	Kenya	0.65
Grimard	1996	the Pakistan development review vol.35(3):257-283	Pakistan	0.44
Halicioglu	2011	working paper. Department of Economics, Yeditepe University	Turkey	0.22
Hoang	2009	working paper. Center for Agricultural Policy, Institute of Policy and Strategy for Agriculture and Rural Development	Vietnam	0.23
Hoddinott etc.	2000	report. International Food Policy Research Institute	Mexico	0.31
Huang	1996	American Journal of Agricultural Economics vol.78(1):21-29	United States	0.27
Irz	2010	Agricultural Economics vol.41:293-304	Finland	-0.01
Jensen and Miller	2011	Review economic statistics vol.93(4):1205-1223	China	0.02
Jha etc.	2011	Journal of Asian Economics vol.22:189-201	India	0.22
Kennedy and Cogill	1987	report No.63 International Food Policy Research Institute	Kenya	0.03
Kennedy and Payongayong	1992	report. International Food Policy Research Institute	Kenya	0.19
Kennedy and Payongayong	1992		Philippines	0.42
Kennedy	1989	report No.78 International Food Policy Research Institute	Kenya	0.16
Knudsen and Scandizzo	1982	American Journal of Agricultural Economics vol.64:80-86	Bangladesh	0.35
			India	0.44
			Indonesia	0.39
			Pakistan	0.34
			Sri Lanka	0.18
			Morocco	0.56
Kochar	2005	Economic development and cultural Change vol.54(1):203-205	India	0.24

Author	p_time	Journal	Country	elasticity
Kumar and Hotchkiss	1988	report No.69.	Nepal	0.51
Li	2012	Southern Economy(Chinese) vol.10:200-215	China	0
Liaskos and Lazaridis	2003	Agricultural Economics Review vol.4(2):93-106	Greece	0.29
Logan	2009	The journal of economic history vol.69(2):388-408	Bangladesh	0.26
			India	0.33
Maxwell etc.	2000	report No.112	Ghana	0.34
McCarthy	1977	Food policy vol.2(1):79-82	Pakistan	0.25
Mushtaq etc.	2007	Pakistan Journal of Nutrition vol.6(2): 159-162	Pakistan	0.21
Ngwenya and Ray	2007	working paper. School of Economics and Finance, University of Tasmania	Indonesia	0.3
Ngwenya	2008	working paper (2008-01) School of Economics and Finance, University of Tasmania	Vietnam	0.41
Ngwenya	2008	working paper (2008-02) School of Economics and Finance, University of Tasmania	Vietnam	0.41
Ohri-Vachaspati etc.	1998	Food policy vol.23(3/4):295-304	Dominican republic	0.21
Orewa and Iyanbe	2010	Academic Journal of Plant Sciences vol.3(4): 147-155	Nigeria	0.13
Ravallion	1990	Economic development and cultural Change vol.38(1):489-515	Indonesia	0.24
Rogers	1996	world development Vol.24(1):113-125	Dominican republic	0.41
Sahn	1988	Economic development and cultural Change Vol.36(2):315-340	Sri Lanka	0.55
Salois etc.	2012	Journal of development studies Vol.48(12):1716-1731	171 countries	0.08
Sarris and Tinios	1994	report Cornell food and nutrition program	Tanzania	0.52
Sinha	2005	working paper. Australian National University	India	0.48
Skoufias	2003	world development Vol.31(7):1291-1307	Indonesia	0.37
Skoufias etc.	2011	Applied Economics vol.43(28):4331-4342	Mexico	0.38
Stillman and Thomas	2004	working paper. Institute for the Study of Labor (IZA), Bonn	Russian Federation	0.07
Strauss and Thomas	1990	working paper. Economic Growth Center, Yale University	Brazil	0.14
Strauss	1982	Journal of development economics vol.14:77-103	Sierra Leone	0.86
Subramanian and Deaton	1996	Journal of Political Economy vol.104(1):133-162	India	0.37
Tian and Yu	2013	Frontiers of Economics in China vol.8(2):186-206	China	0.08
Tiffin and Dawson	2002	Journal of agricultural economics vol.53(2):221-232	Zimbabwe	0.31
Trairatvorakul	1984	report No.46 International Food Policy Research Institute	Thailand	0.21
Ulimwengu etc.	2012	working paper. International Food Policy Research Institute	Congo, Dem. Rep.	0.82
Vecchi and Coppola	2004	Explorations in Economic History vol.43:438-464	Italy	0.36
Von Braun etc.	1989	report No.75. International Food Policy Research Institute	Gambia, The	0.42
Vu	2008	dissertation Faculty of the Graduate School, University of Minnesota	Vietnam	0.23
Wang	2011	working paper. Huazhong University of Science and Technology	United States	0.09
Ward and Sanders	1980	Economic development and cultural Change	Brazil	0.37

Author	p_time	Journal	Country	elasticity
		vol.29(1):141-164		
Cheryl Williamson Gray	1982	report No.32 International Food Policy Research Institute	Brazil	0.2
Wolfe and Behrman	1983	Economic development and cultural Change vol.31(3):525-549	Nicaragua	0.01
Yu etc.	2012	Food and Nutrition in China(Chinese) vol.18(9):41-44	China	0.36
Zheng and Henneberry	2012	China Economic review vol.23:1090-1103	China	0.95
Zhong etc.	2012	China Economic review vol.23:1011-1019	China	0.04
Dawson	1997	Oxford development studies vol.25(3):361-369	41 developing countries	0.07

Note: elasticity is the mean of calorie-income elasticities in the primary study

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