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

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Calorie Elasticities with Income Dynamics: Evidence from the Literature

Abstract:

This paper proposes a finite mixture model (FMM) to model the behavioral transition of calorie consumption with an assumption that nutrition consumption is a mixture of two different behavioral stages: a poor stage and an affluent stage. Based on 387 calorie-income elasticities collected from 90 primary studies, our results identify that 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).

Keywords: nutrition transition, calorie consumption, income elasticity, finite mixture model

JEL code: D12

1 Introduction

The studies on nutrition demand has 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). The central piece of economic development literature on nutrition demand is located on the relationship between income and calories consumption: how could income growth 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 generally can alleviate undernutrition and hunger particularly in developing countries, and 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 1998a, 1998b, 1999, and 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. 2012, etc.) to almost one (e.g. Pitt 1983; Strauss 1984; Behrman et al. 1997, etc.). 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 in 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 is gently declining as income increases and households that are above the median income would spend additional earning to buy higher quality food, rather than a pure increase in calories consumption. Tian and Yu (2013) find that the calorie-income elasticity is 0.32 and statistically significant for consumers in China with income below the moderate poverty line ($2/day), and then downs to 0.064 and statistically insignificant when income is above the poverty line. 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 clear enough so far, 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,, so that they tend to buy the cheapest food (e.g., cassava, wheat and rice which are 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 will pay more attention to the non-calorie attributes rather than to pursue 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). 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; Jensen and Miller 2011). It 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 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 often 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 the structural changes in 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: the poor's and the rich's behaviors, and assign a probability for each behavior. If the probability of the poor's behavior is higher than that of the rich's, we define 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 the income elasticities 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 mixture of 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).

The rest of this paper is organized as follows: Section 2 presents the economic model with incorporation of the FMM; Section 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; finally, the paper is concluded in Section 5.

2 Empirical strategy

Common wisdom tells us that calorie consumption is dynamic with income growth, and has a nonlinear relationship with income: calorie intake increases rapidly at the poor stage and then tends to become less sensitive at the affluent stage with an increasing income, as it converges to a saturation point due to biological reasons. Correspondingly, with income growth, calorie elasticity with respect to income first declines rapidly as the marginal utility of additional calories goes down significantly and eventually stays at a very low level. Hence, calorie-income elasticities can be used for measuring behavior of nutrition transition. The changes in calorie intake and corresponding calorie-income elasticities are depicted in Figure 1.

[Insert Figure 1]

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 the basic needs for food consumption and nutrition requirements are not contented. They suffer from hunger and the marginal utility of additional calories is very high at the poor stage. Once they enter the affluent stage, consumers will switch to a strong preference for palatable and high quality foodstuffs (Behrman et al. 1997;Behrman and Deolalikar 1987; Subramanian and Deaton 1996;Jensen and Miller 2011).

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 definitions of the rich and the poor are also relative. It is very difficult to distinguish them simply by a cut-off number of per capital income. For instance, different countries have different definitions of poverty lines (Chen and Ravallion 2010), even though the poverty line set by the World Bank is 1.25 $/day in terms of 2005 PPP (Purchasing Power Parity) price. For instance, 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.

As is indicated in Figure 1, when income is very low, the income elasticity for a consumer is relatively high. The consumer will spend most of their additional income in food at the poor stage and the calorie intake grows rapidly. However, once the consumer passes the threshold of subsistent level, and enters the affluent stage, the income elasticity decreases rapidly, and eventually stays relatively low. The elasticity becomes inactive with further income growth. As aforementioned, the threshold is usually unobserved and varies across different groups, so that it lies in an 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 explicitly unobserved. However, such as assumption later will be tested ex post with our data. The two behavior functions are defined as follows:

$$CE_{k,j} = g_k\left(Y_j, X_j\right) + \varepsilon_{k,j} \tag{1}$$

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.

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 mixed 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

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

In equation (2), one can speculate that π_h is positively correlated with income. In contrast, π_l declines as income increases. That is, as income increases, the probability that a consumer performs as the poor-stage behavior 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 (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

$$f(CE \mid Y, X, \theta) = \pi_l f(CE \mid Y, X, \theta_l) + \pi_h f(CE \mid Y, X, \theta_h) \tag{3}$$

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 $\pi^T = (\pi_l, \pi_h)$, $\pi_k > 0, \sum \pi_k = 1$ and $\theta_k = (\beta_k', \sigma_k^2)'$. In order to estimate Equation (3), the model must assume a constant prior probability of a component group across all observations. Once we have the estimates of 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

$$P(k \mid CE, Y, X, \varphi) = \frac{\pi_k f(CE \mid Y, X, \theta_k)}{\sum \pi_k f(CE \mid Y, X, \theta_k)} \tag{4}$$

Thus, the posterior probability varies across observations and could be further used for examining the dynamics of calorie demand transition, and 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 performs at the poor stage declines as income increases. Herein, it is plausible to assume the posterior probability follows a logistic growth curve

$$P_l = \frac{e^{Z\beta+e}}{1+e^{Z\beta+e}} \tag{5}$$

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

Rewriting Equation (5) yields an estimatable function,

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

After estimating Equation (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 threshold income level.

3 Dataset

- **Sources**

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 and yield 387 estimated income elasticities of calorie consumption (intake). Figure 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.

[Insert Figure 2]

- **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 dynamic of their relationships 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 deflated to 2012 prices with the consumer price index 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, 2010b; 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 generally are 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 nutrients 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 [1] and food diary, 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

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

estimates a food demand system for a number of food groups and then converts the resulting food-income elasticities to 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.

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.

- **Descriptive statistics**

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

[Insert Table 1]

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 indirect method are substantially higher than from 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 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 scatter plot. The result is presented in Figure 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.

[Insert Figure 3]

A straightforward way to check if the FMM is an appropriate model is to test the distribution of the residuals of OLS regression. The distribution of the OLS residuals is depicted in Figure 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[2]. Therefore, consistent with our hypothesis, we observed two components in our sample.

[Insert Figure 4]

The results are reported in Table 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. The 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 other things being constant. That implies component 1 mainly consists of the low-income consumer group that usually pay more attention to the price and quantity of calories.

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 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 food and expensive source of calories. .

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

We could approximate the posterior probability of each component for each observation based on the estimation of Equation (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 in 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 5 shows that the posterior probabilities of being component 1 and log real income are negatively correlated. The estimation results of Equation (6) for the posterior probability function are reported in Table 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 (6), we could use the full model to predict the threshold income level of calorie demand transition with an assumption of other variables at mean values.

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 around1.26 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). It 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 of 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 other 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), that 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.

[Insert Table 2, 3]

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. That implies 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 a lower calorie-income elasticity.

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 the calorie-income elasticity is still debatable. In order to fulfill the gap in the current literature, this paper 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 calories consumption.

We collected 387 estimated calorie-income elasticities from 90 primary studies, which are used for the analysis in this paper, 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 generally 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 of the poverty line set by the World Bank.

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

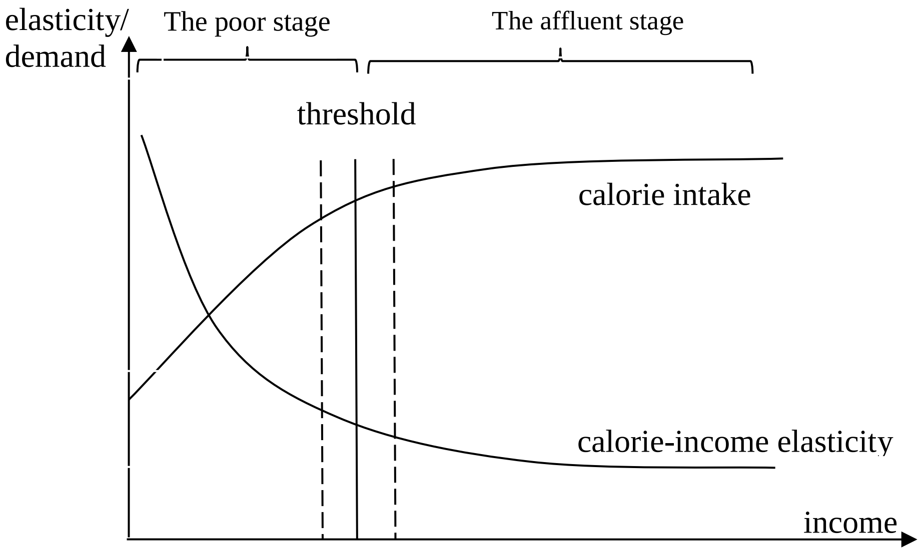
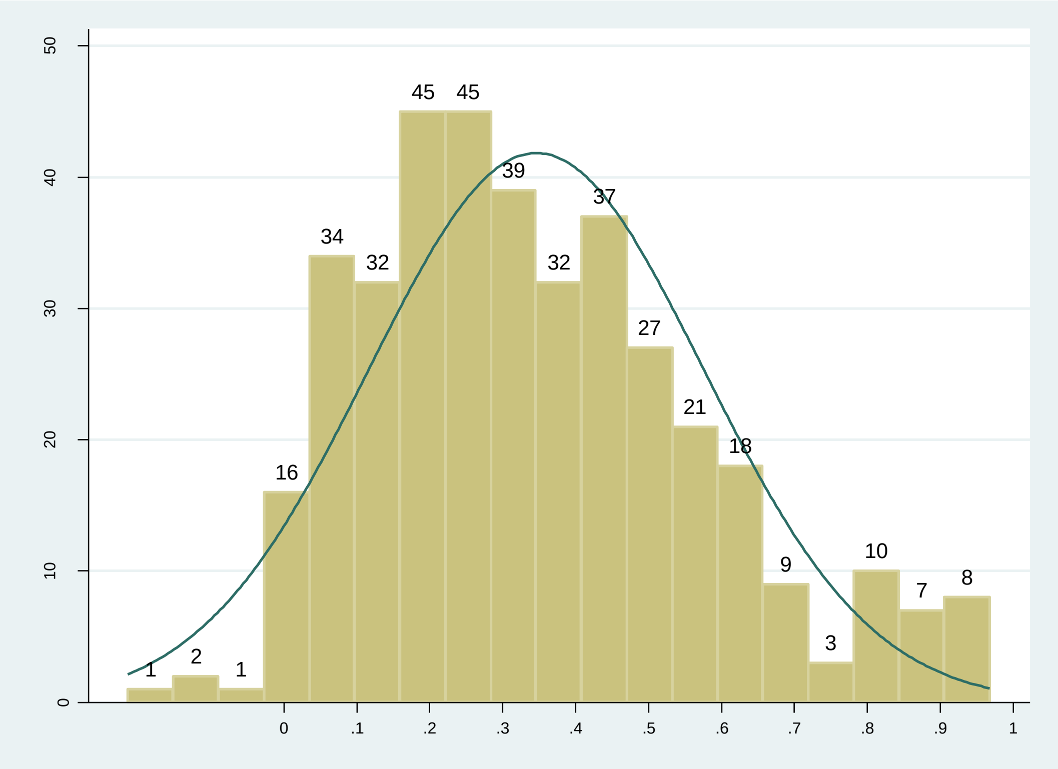


Figure 2. The distribution of the estimated calorie-income elasticities in the primary studies



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

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

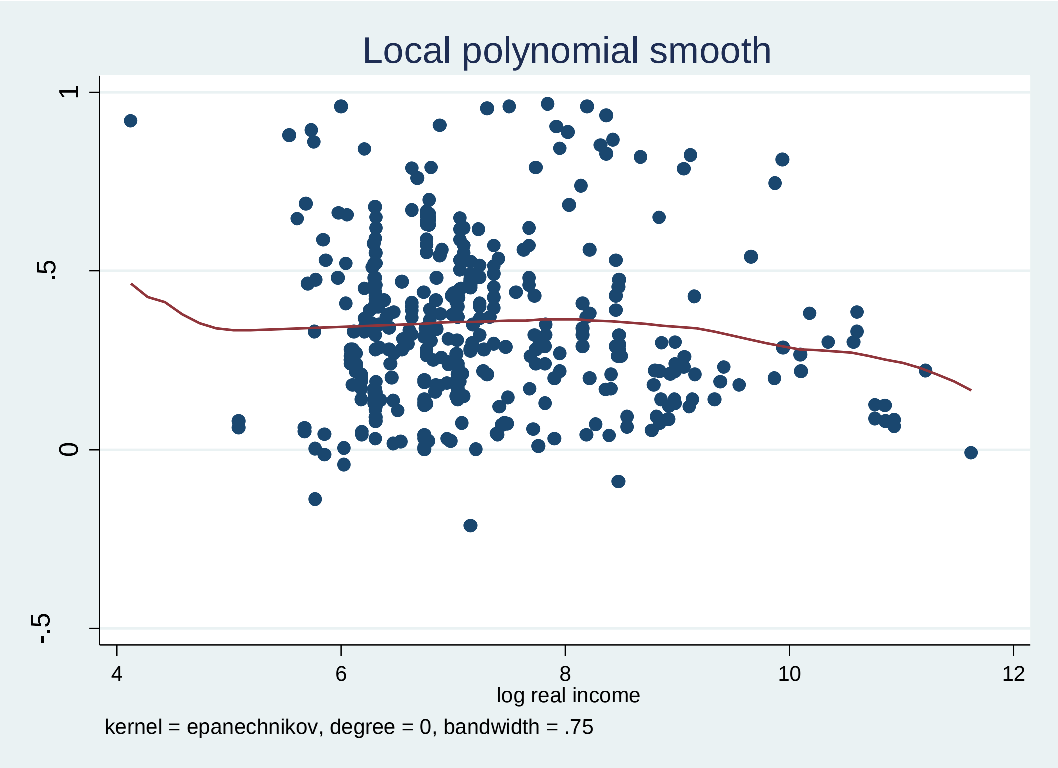
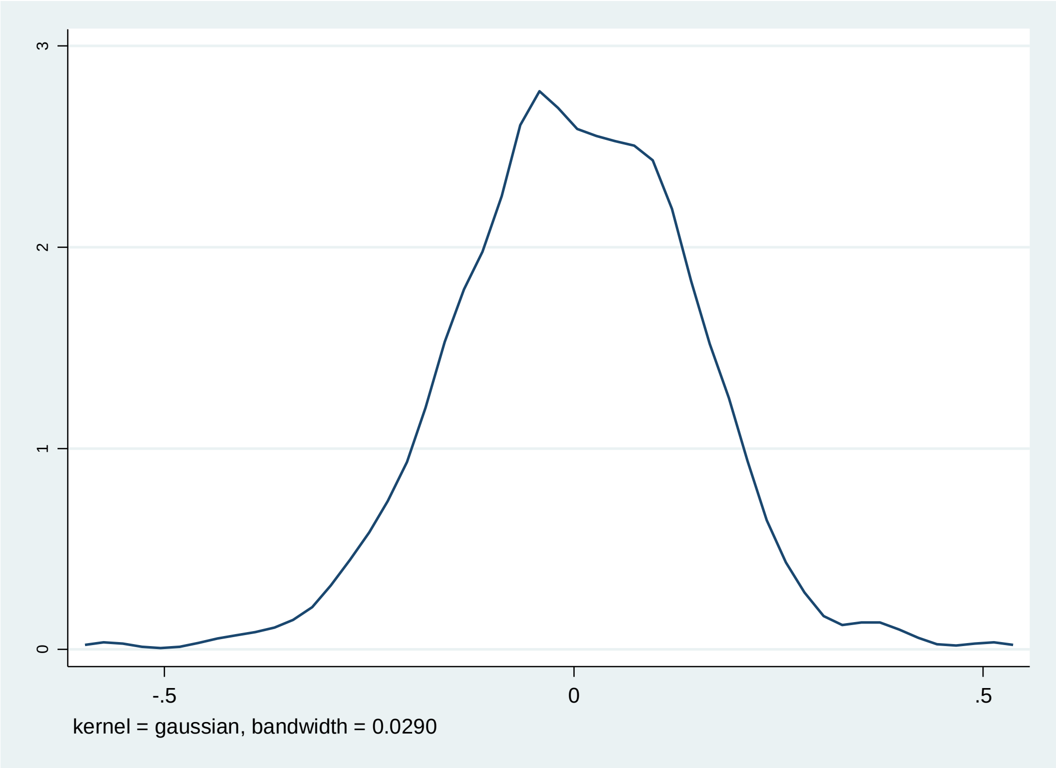


Figure 4. Kernel density of OLS residuals from calorie-income elasticity regression



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

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

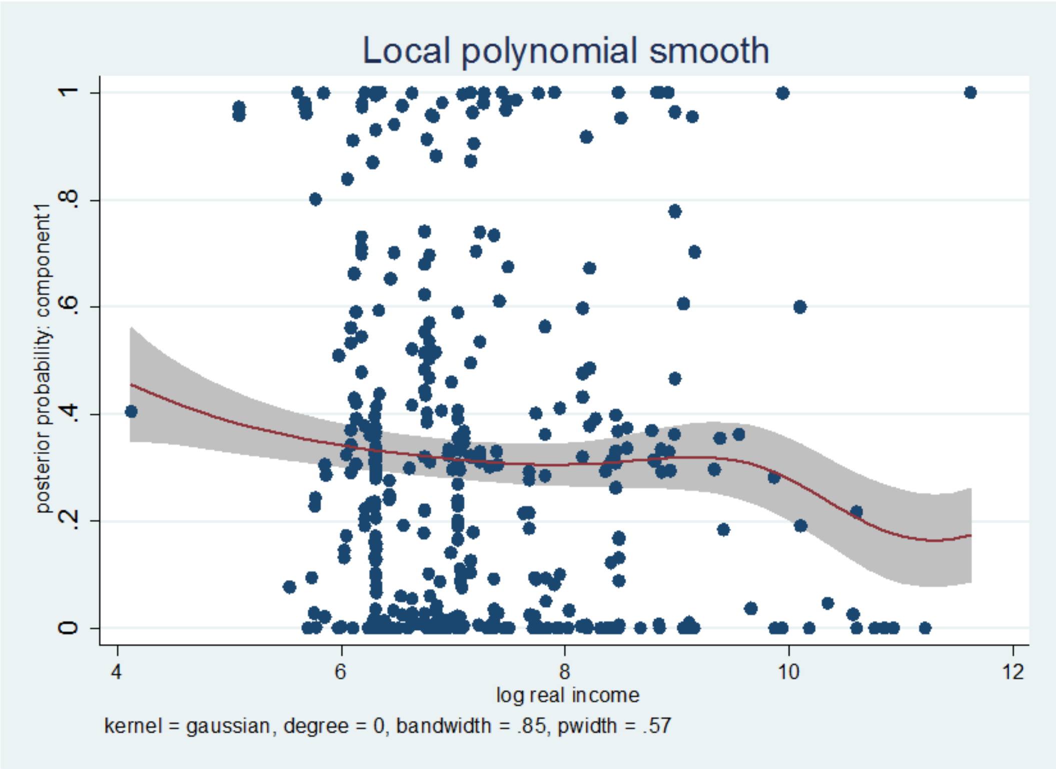


Table 1 Summary statistics of the calorie-income elasticities by study characteristics

	Variable	Definition	Obs	Mean
Pooled	elasticity	reported calorie-income elasticity	387	0.346
publication	pub_wp	Dummy for working/ discussion paper	104	0.372
	pub_journal	Dummy for the study published in journal	218	0.336
	pub_report	Dummy for the report or book chapter (reference)	65	0.339
Region	r_asia	Dummy for the study was carried out in Asia	192	0.314
	r_africa	Dummy for the study was carried out in Africa	90	0.422
	r_oth	Dummy for the study was carried out in other region (reference)	105	0.340
Data	d_cross	Dummy for the use of cross-section data	202	0.389
	d_times	Dummy for the use of time series data	17	0.208
	d_panel	Dummy for the use of other data (reference)	168	0.308
	cond_inc	Equal to 1 if the study used actual income	69	0.178
	cond_exp	Equal to 1 if the study used expenditure as proxy for income (reference)	318	0.382
	cond_intakes	Equal to 1 if calorie is measured via the intake based on food consumption	132	0.277
	cond_intakes0	Dummy for calorie is measured via the availability of food (reference)	255	0.382
	lnrealinc	The log real income (base year 2012$)	387	7.265
Survey	survey_days	Dummy for the daily nutrition survey which covers less than 72 hours food recall	83	0.152
	survey_week	Dummy for the weekly nutrition survey which covers less than 2 weeks food recall	113	0.381
	survey_oth	Dummy for other nutrition survey (reference)	191	0.410
Method	m_direct	Equal to 1 if the study used direct approach	330	0.302
	m_indirect	Equal to 1 if the study used indirect approach (reference)	57	0.603
	ivreg	Equal to 1 if the study used instrumental variable regression	68	0.235
	ivreg0	Dummy for the study didn't use instrumental variable regression (reference)	319	0.370
	est_ols	Dummy for the use of OLS estimation	215	0.372
	est_ml	Dummy for the use of ML estimation	25	0.506
	est_other	Dummy for the use of other method (reference)	147	0.281

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

	OLS	FMM	
		component1	component2
pub_j	0.098***	-0.131**	0.125***
	(0.02)	(0.06)	(0.03)
pub_wp	0.063**	-0.337***	0.116***
	(0.03)	(0.10)	(0.03)
r_asia	-0.095***	-0.347***	-0.095***
	(0.02)	(0.08)	(0.03)
r_africa	0.070**	-0.098	0.038
	(0.03)	(0.07)	(0.04)
d_times	-0.312***	0.109	-0.538***
	(0.05)	(0.11)	(0.09)
d_cross	0.011	0.088	-0.057**
	(0.02)	(0.06)	(0.03)
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)
cond_inc	-0.105***	-0.332***	0.002
	(0.02)	(0.04)	(0.06)
cond_intakes	-0.022	0.028	0.007
	(0.02)	(0.05)	(0.04)
m_direct	-0.282***	-0.056	-0.317***
	(0.02)	(0.06)	(0.03)
Ivreg	-0.058**	-0.054	-0.046
	(0.03)	(0.05)	(0.04)
est_ols	0.030	0.013	0.019
	(0.02)	(0.04)	(0.04)
est_ml	0.145***	-0.159*	0.297***
	(0.04)	(0.09)	(0.06)
lnrealinc	**-0.032*** **	**-0.121*** **	**-0.023**
	(0.01)	(0.03)	(0.01)
Intercept	0.867***	1.655***	0.864***
	(0.08)	(0.33)	(0.14)
σ		-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: 1.Standard errors are provided in parentheses.
2.Levels of significance:***=1%, **=5%, and *=10%

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

	pos1(1)	pos1(2)	pos1(3)
Lnrealinc	-1.617***	-1.896***	-1.733***
	(0.28)	(0.34)	(0.34)
r_asia		-1.357	-1.542
		(0.93)	(0.96)
r_africa		-1.134	-1.447
		(1.07)	(1.13)
pub_j			0.348
			(0.92)
pub_wp			-1.631
			(1.02)
d_times			7.411***
			(2.05)
d_cross			-0.877
			(0.71)
survey_days			-1.849*
			(0.99)
survey_week			-0.642
			(0.79)
cond_inc			-2.662***
			(0.93)
cond_intakes			0.583
			(0.84)
m_direct			3.686***
			(0.98)
Ivreg			-0.464
			(1.05)
est_ols			-1.087
			(0.84)
est_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%
. 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.

Appendix table: Summary statistics of the primary studies

Author	p_time	Journal	Country	elasticity
Abdulai and Aubert	2004	Food policy vol.29:113-129	Tanzania	0.52
Abudulai and Aubert	2002	wp	Tanzania	0.57
Abudulai and Aubert	2004	Agricultural Economics vol.31:67-79	Tanzania	0.43
Alderman and Higgins	1992	wp	Ghana	0.51
Alderman etc.	1988	report	Pakistan	0.39
Alderman	1987	report	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	wp	Nigeria	0.08
Ayalew	2000	wp	Ethiopia	0.14
Babatunde	2008	wp	Nigeria	0.16
Babatunde etc.	2010	Agricultural Science vol.2-2:135-146	Nigeria	0.18
Basu and Basole	2012	wp	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	Ifpri report	Guatemala	0.31
Braun etc.	1991	Ifpri report	Rwanda	0.48
Chernichovsky and Meesook	1987	WB report	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	wp	Bulgaria	0.78
Djebbari	2005	wp	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	Ifpri report	Sri Lanka	0.42
Gaiha etc.	2010	wp	India	0.34
Gaiha etc.	2010	wp	India	0.08
Gaiha etc.	2012	wp	India	0.33
Garcia and Pinstrup-Andersen	1987	Ifpri report	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	wp	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	wp	Turkey	0.22
Hoang	2009	wp	Vietnam	0.23
Hoddinott etc.	2000	Ifpri report	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	Ifpri report	Kenya	0.03
Kennedy and Payongayong	1992	Ifpri report	Kenya	0.19
Kennedy and Payongayong	1992	Ifpri report	Philippines	0.42
Kennedy	1989	Ifpri report	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
Kumar and Hotchkiss	1988	Ifpri report	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	Ifpri report	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	wp	Indonesia	0.3
Ngwenya	2008	wp	Vietnam	0.41
Ngwenya	2008	wp	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	Indonesia	0.24

		vol.38(1):489-515		
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	Cornell food and nutrition program	Tanzania	0.52
Sinha	2005	wp	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	wp	Russian Federation	0.07
Strauss and Thomas	1990	wp	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	Ifpri report	Thailand	0.21
Ulimwengu etc.	2012	Ifpri report	Congo, Dem. Rep.	0.82
Vecchi and Coppola	2004	Explorations in Economic History vol.43:438-464	Italy	0.36
Von Braun etc.	1989	Ifpri report	Gambia, The	0.42
Vu	2008	dissertation	Vietnam	0.23
Wang	2011	wp	United States	0.09
Ward and Sanders	1980	Economic development and cultural Change vol.29(1):141-164	Brazil	0.37
Gray	1982	Ifpri report	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