Is Urban Food Demand in the Philippines Different from China?

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1 Introduction

Food is an essential good, and thus understanding its demand is important for the formulation of sound agricultural policies and developing sustainable agricultural business. A timely analysis of food demand is important because it can change over time not only because prices and incomes change but also because people's taste itself also change. However, even in countries where food accounts for a sizable share of expenditure or where the agricultural sector accounts for a large share of output, careful analysis of food demand is often not readily available.

In this study, we analyze the food demand in urban Philippines and compare it to the one in China. This comparison is interesting for two reasons. First, there are some similarities between Filipino and Chinese food cultures. This is not surprising, because Filipino cuisine has been significantly influenced by Chinese cuisine. The similarities are particularly pronounced in lower- and middle-class cuisine because the Chinese first came as traders, settlers, and merchants. For example, dishes like noodles, certain sausages, vegetables wrapped in a thin rice wrapper, and meat encased in dough come from the Chinese cuisine and have been widely absorbed in the Filipino cuisine and cooked in homes and eateries (see Fernandez 1986).

Second, the economic growth in China has been much faster than the Philippines in recent years. For example, according to the World Development Indicators published by the World Bank, China's GDP per capita in constant 2011 international dollars is $1554 in 1990 and $9230 in 2010. The corresponding figures for the Philippines are $4010 in 1990 and $5613 in 2010. Therefore, we may expect to see more pronounced changes in China than in the Philippines over the last two decades or so.

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There are, however, two important limitations to this argument. First, the Filipino food culture has also been heavily influenced by the Spanish food culture, but this is not applicable to the Chinese food culture. Therefore, the westernization of food culture has started much earlier in the Philippines. Second, the food culture in China is very diverse in itself. For historical reasons, the Chinese influence did not uniformly come from China. Most notable influences come from southern China, particularly around the current Fujian province. Despite these limitations, the structural changes in food demand China has experienced tell us some directions in which the structural changes in food demand are likely to take place in the Philippines. This is particularly true, if the Philippines were to catch up with China in GDP per capita in the future.

We analyze the food demand by estimating the Quadratic Almost Ideal Demand System (QUAIDS) proposed by Banks et al. (1997) with various rounds of the Family Income Expenditure Survey (FIES) using a variant of the iterated linear least-squares estimator developed by Blundell and Robin (1999). Besides the obvious empirical contributions, we improve on the existing method by estimating the QUAIDS for a relatively large number of goods in a reasonably efficient manner by using the conditional linearity of the estimation equations, by taking advantage of the variance–covariance matrix of the unobserved error term, and by directly imposing the restrictions on the parameters required by economic theory.

This paper is organized as follows. We first review relevant existing studies on food demand in the Philippines and China in the next section. In Sect. 3, we present the methodology used in this study. In Sect. 4, we describe the data followed by the results in Sect. 5. Section 6 offers some discussion including some policy and business implications.

2 Review of Existing Studies

To facilitate the discussion later, we provide a review of some of the important studies on food demand in China and the Philippines in this section.

2.1 China

There are an increasing number of studies on food demand in China, especially in urban China in recent years. This is not surprising because the changes in the food demand structure in China affect not only the food market in China but also the rest of the world. Here, we discuss a few studies that are most closely related to ours.

The study by Gould and Villarreal (2006) is one of the recent studies that adopt the QUAIDS. They use it to analyze the structure of food demand in four urban provinces in China. According to their estimates, beef, poultry, and grains other than rice are among the food categories with relatively high uncompensated own-price elasticities. For most food items, the differences in expenditure elasticities and uncompensated own-price elasticities across different income groups were small. They also examined the importance of food at home and food away from home and found that the latter tends to increase with the household's income level.

Zheng and Henneberry (2010) estimate food demand only in the urban Jiangsu province. They find that there is no obvious difference in own-price elasticity across different income groups and that the income elasticity tends to be lower for wealthier households. Based on these estimates, they project the future food demand. They emphasize the importance of income distribution in demand projection as more equal distribution would imply higher food demand even when the average income remains the same. In a separate study, Zheng and Henneberry (2011) argue that the researchers should use the demand parameter that pertains to the relevant income group for the appropriate design of policies and marketing strategies for the population group of interest, because the constant elasticities of food demand among income groups are not supported in the urban Jiangsu province. These studies highlight the potential importance of addressing the heterogeneous elasticities across different income groups.

Another study that is closely related to ours is Dong and Fuller (2010). Using the Almost Ideal Demand System (AIDS) developed by Deaton and Muellbauer (1980), they analyze the shift in consumer demand in urban China between 1981 and 2004 with aggregate data. They find that changes in grain consumption can be largely explained by normal price and income effects. On the other hand, they find some evidence for structural change in the demand of meat, vegetables, fruits, and fish, which played a less important role in daily food consumption in traditional Chinese diets.

Similarly, Hovhannisyan and Gould (2014) use provincial-level data in urban China and test the structural change in food demand between 2002 and 2010. They find evidence that urban Chinese diet preferences have changed in their study period. Namely, they find that the magnitudes of uncompensated own-price elasticities in the seven food categories (meat, seafood, vegetables, fruits, grain, eggs, and fats) they used have decreased with an exception of eggs. These decreases are most apparent in the demand of fruits and meats, which points to their rising importance in the urban Chinese food diet.

Hovhannisyan and Gould (2011) also analyze the structural change in demand using household-level expenditure surveys for 1995 and 2003. Based on an independent test of equality, they find that uncompensated own-price elasticity has changed statistically significantly for all goods, except for beef and poultry, and became less elastic for seafood, vegetables, fruits, rice, and dairy products in their study period. Our approach is similar to Hovhannisyan and Gould (2011) in the sense that we use household-level data and a similar test for the presence of structural change.

The empirical evidence from these studies provides at least three important implications for our study. First, controlling for demographic characteristics of the household is potentially important. While this is not surprising, it is important in practice. Second, both price and budget elasticities, especially the latter, appear to depend on whether the household is rich or poor to some extent. Therefore, we provide disaggregate results by the expenditure quintile. Third, while the estimated elasticities vary substantially across studies and their direct comparisons are difficult because of the differences in the geographic coverage, study periods, and methodologies used, they tend to find lower budget elasticities over time for most food items. On the other hand, the changes in price elasticities appear to be heterogeneous across food items. We will subsequently verify that this is also the case in the Philippines.

2.2 Philippines

There have been several studies on food demand in the Philippines to date. One of the earliest studies based on household surveys is Quisumbing et al. (1988). They use two household surveys conducted by the Food and Nutrition Research Institute in 1978 and 1982 to estimate food subsystem and the cross-tabulations taken from four rounds of FIES in 1961, 1965, 1971, and 1975 to estimate a translog expenditure system for five groups of goods.

Bouis (1990) proposes a demand system based upon a utility function that is additive in bulk, variety, and tastes of individual goods and applies it to the Philippines. His estimates show that meat tends to have high own-price elasticity and income elasticity whereas corn is estimated to have a negative income elasticity both in urban and rural areas. Similarly, Bouis et al. (1992) show that both caloric intake (computed from 24-h recall survey) and caloric availability (computed from food expenditure survey) tend to be higher for richer households for most food items, but this is not the case for corn.

Balisacan (1994) reviews earlier studies on food demand in the Philippines and estimates the AIDS using three rounds of the FIES data in 1985, 1988, and 1991. He finds that food items are generally income inelastic. In particular, rice, the major staple, has an income elasticity of 0.08. On the other hand, corn has a negative income elasticity, a pattern that is consistent with abovementioned studies.

A more recent estimate is provided by Mutuc et al. (2007). They use FIES data for year 2000 to estimate a QUAIDS with a detailed disaggregation of vegetables. They find significant difference between the expenditure elasticities of urban and rural households, whereas they did not find statistical difference between urban and rural households in own- and cross-price elasticities.

Our study is different from these earlier studies in several respects. First, many of the studies mentioned above, including those in China, either (1) assume separability between food and non-food items or (2) highly aggregate non-food items. However, the separability assumption is not a harmless assumption because the total budget for the food may be endogenous. Aggregation of non-food items may appear more innocuous, but the aggregability requires some (strong) assumptions on the utility function. When we lump a variety of non-food goods together, the aggregability is less likely to hold even as an approximation. We avoid this issue by directly estimating a demand system with a relatively large number of goods.

Second, unlike the studies mentioned above, we use more recent rounds of FIES data. Therefore, our results provide an update on the elasticity estimates. Finally, we estimate elasticities over a long study period using a consistent methodology. This allows us to understand the changes in the structure of food demand. As far as we are aware, no study has investigated the changes in food demand structure in the Philippines using recent data.

3 Methodology

We estimate the demand system using the Quadratic Almost Ideal Demand System (QUAIDS) proposed by Banks et al. (1997), which has become a standard model of the analysis of demand systems. The QUAIDS model nests the AIDS model and retains its attraction of exact aggregability. The QUAIDS model has additional flexibility due to the quadratic logarithmic income term. As a result, some goods may be necessities at some income levels or luxuries at others in the QUAIDS model.

Both the AIDS and QUAIDS model can be in principle estimated by the standard estimation methods such as the maximum likelihood estimation (MLE). As is well known, the computational cost of MLE substantially increases as the number of parameters to be estimated goes up. Furthermore, the non-convergence issue is more likely to occur when the parameter space is high dimensional. These issues can be very serious, when the number of goods in the demand system is just moderately large, because the number of parameters to be estimated can inflate quickly. For example, without any additional regressors, the number of parameters to be estimated in the standard QUAIDS model is only 22, 72, and 247 when the number of goods in the system is 5, 10, and 20, respectively.

Therefore, applied researchers interested in the demand system of a particular set of disaggregate goods tended to deal with this issue (1) by focusing on a subset of the goods assuming some form of separability or (2) by aggregating the goods that are not of their main interest. The first approach is problematic when separability does not hold. The second approach is also problematic when the goods are not aggregable.

Blundell and Robin (1999) address this problem by estimating a large demand system without numerical maximization in the following manner: because QUAIDS model is conditionally linear, we can estimate the parameter by an ordinary least-squares (OLS) regression of the expenditure shares, taking some price indices as given. Then, these price indices are “updated” with the estimated coefficients. Using the updated price indices, we run an OLS regression again. This iteration continues until convergence is attained. The iterated linear least-squares (ILLS) estimator thus obtained is straightforward to implement and runs fast enough for practically large models as demonstrated by Blundell and Robin

(1999). In this study, we use a modified version of this estimator, which we refer to as the iterated generalized linear least-squares (IGLLS) estimation. As the name suggests, we run a (feasible) generalized least-squares (GLS) regression instead of an OLS regression in each iteration.

Our method runs comparably fast and yields more accurate estimates for two reasons. First, we impose the symmetry of the Slutsky matrix in the iterated regressions. This contrasts with the minimum chi-square estimator developed by Ferguson (1958), which is used to impose constraints after an unconstrained estimator is obtained. While the minimum chi-square estimator is asymptotically as efficient as the MLE under some restrictive assumptions (Rothenberg 1973), it is not generally so in a finite sample. This issue may be particularly severe when the variance–covariance matrix of the unrestricted estimator is not reliable. Second, we use the variance–covariance matrix of the residuals in the iterative procedure, so that the weights used in the regression are asymptotically optimal.

In this section, we first develop the IGLLS estimator. Because this is a straightforward extension of the ILLS estimator and their derivations are very similar, we shall keep this discussion short. We then discuss how the IGLLS estimator is used to estimate the QUAIDS.

3.1 Definition and Asymptotic Properties of the IGLLS Estimator

Let x_h and u_h be a real column M-vector of control variables and a real column K-vector of random error terms, respectively, for household $h \in \{1, \ldots, H\}$. We assume that the pair x_h, u_h is independently and identically distributed and that $E\left[u_h \middle| x_h\right] = \mathbf{0}_K$ holds for all h, where $\mathbf{0}_K$ is a column K-vector of zeros. The outcome variables of interest are a real column K-vector y_h, where y_h satisfies $y_h = g(x_h, \theta_0)\theta_0 + u_h$ for some true parameter value $\theta_0 \in \Theta$ contained in the parameter set Θ, which is an open and convex set on $\mathbf{R}^D$. We further assume that $g : \mathbf{R}^M \times \Theta \rightarrow \mathbf{R}^{K \times D}$ is a twice continuously differentiable function with respect to $\theta\left(= \left[\theta^1, \ldots, \theta^D\right]^T\right)$, where we use a superscript to denote each vector component except that T is used as a transpose operator.

For the simplicity of notation, we define a few additional notations. First, we denote the non-singular finite weighting matrix by $W(\theta) \equiv E^{-1}\left[(y_h - g(x_h, \theta)\theta)(y_h - g(x_h, \theta)\theta)^T\right]$ and also define $W_0 \equiv W(\theta_0) = E^{-1}\left[u_h u_h^T\right]$. Second, we use capital letters to denote stacked observations such that we have $Y \equiv \left[y_1^T, \ldots, y_H^T\right]^T$ and $U \equiv \left[u_1^T, \ldots, u_H^T\right]^T$. Finally, with a slight abuse of notation, we also define $G(\theta) \equiv \left[g^T(x_1, \theta), \ldots, g^T(x_H, \theta)\right]^T$. By definition, we have the following relationship:

$$Y = G(\theta_0)\theta_0 + U. \tag{1}$$

Notice that Eq. (1) is a standard linear equation once $G(\theta_0)$ is taken as given. The basic idea of the ILLS estimator is essentially built on this idea. That is, if we have an estimate $\hat{\theta}^{(p)}$ of θ in the pth iteration, then we can "update" the estimator by running the ordinary least-squares (OLS) estimation. However, this estimation is bound to be inefficient when u_h is correlated across h. This is indeed likely in the estimation of demand system because the error terms across goods are likely. Hence, instead of running OLS, we run a feasible generalized least-squares (FGLS) regression in each iteration to obtain a more efficient estimate.

To do so, we first estimate the weighting matrix $\hat{W}\left(\hat{\theta}^{(p)}\right)$ given $\hat{\theta}^{(p)}$ by the following equation:

$$\hat{W}\left(\hat{\theta}^{(p)}\right) \equiv \left[\frac{1}{H-1}\sum_h \left(y_h - g\left(x_h, \hat{\theta}^{(p)}\right)\hat{\theta}^{(p)}\right)\left(y_h - g\left(x_h, \hat{\theta}^{(p)}\right)\hat{\theta}^{(p)}\right)^T\right]^{-1}. \tag{2}$$

Then, we run an FGLS regression conditional on $G\left(\hat{\theta}^{(p)}\right)$ in Eq. (1) using $\hat{W}\left(\hat{\theta}^{(p)}\right)$ in Eq. (2) as a weighting matrix to obtain a new (updated) estimator in the following manner:

$$\hat{\theta}^{(p+1)} = \left[G^T\left(\hat{\theta}^{(p)}\right)\left(I_H \otimes \hat{W}\left(\hat{\theta}^{(p)}\right)\right)G\left(\hat{\theta}^{(p)}\right)\right]^{-1}\left[G^T\left(\hat{\theta}^{(p)}\right)\left(I_H \otimes \hat{W}\left(\hat{\theta}^{(p)}\right)\right)Y\right], \tag{3}$$

where I_H is an $H \times H$-identity matrix and $\otimes$ is the Kronecker-product operator.

Therefore, once we have an initial estimate $\hat{\theta}^{(0)}$, we obtain a sequence of estimates $\hat{\theta}^{(0)}, \hat{\theta}^{(1)}, \hat{\theta}^{(2)}, \ldots$ by continuing the iteration. We obtain our iterated generalized linear least squares (IGLLS) as a limit of this sequence. Notice that the only difference between the IGLLS and ILLS is the presence of weighting. Therefore, if we use I_K instead of $\hat{W}\left(\hat{\theta}^{(p)}\right)$ in Eq. (3), we obtain the ILLS estimator.

Because IGLLS is taken as a limit of the sequence, the IGLLS estimator $\hat{\theta}$ satisfies the following equation by construction:

$$\hat{\theta} = \left[G^T(\hat{\theta})\left(I_H \otimes \hat{W}(\hat{\theta})\right)G(\hat{\theta})\right]^{-1}\left[G^T(\hat{\theta})\left(I_H \otimes \hat{W}(\hat{\theta})\right)Y\right]. \tag{4}$$

It can be shown that $\hat{\theta}$ is a consistent estimator of θ_0 and asymptotically normally distributed under suitable regularity conditions as shown in the following theorem:

Theorem 1 *Let* $\mathbf{e}_d$ *be a row* D*-vector whose dth component is one and all the other components are zero and define the following quantity:* $h(x_h, \theta_0) \equiv \sum_d \frac{\partial g(x_h, \theta_0)}{\partial \theta^d} \theta_0 \mathbf{e}_d$,

whose dth column vector is the partial derivative of g with respect to the dth component of θ *multiplied by* θ_0*. Further define*

$$M_0 \equiv E\left[g^T(x_h, \theta_0) W_0 g(x_h, \theta_0)\right] \text{ and } Q_0 \equiv M_0 + E\left[g^T(x_h, \theta_0) W_0 h(x_h, \theta_0)\right].$$

Then, under suitable regularity conditions, $\hat{\theta}$ *given in* Eq. (4) *satisfies*
$\hat{\theta} \xrightarrow{a.s.} \theta_0$ and $\sqrt{H}(\hat{\theta} - \theta) \xrightarrow{d} N\left(0, Q_0^{-1} M_0 Q_0^{-T}\right)$.

The asymptotic variance can be estimated by replacing θ_0 with its estimate $\hat{\theta}$ in Q_0 and M_0 above.

3.2 Application of the IGLLS Estimator to the QUAIDS

We now apply the IGLLS estimator to the QUAIDS. Suppose that there are N goods in the economy, and denote the column N-vector of the logarithmic prices by $p \equiv [p^1, \ldots, p^N]^T$. We let the logarithmic expenditure be m. The QUAIDS proposed by Banks et al. (1997) follows from the following indirect utility function:

$$\ln v\,(m, p) = \left(\left[\frac{m - a(p)}{b(p)}\right]^{-1} + c(p)\right)^{-1}, \tag{5}$$

which is an extension of the price-independent generalized logarithmic (PIGLOG) indirect utility function used by Muellbauer (1976) and satisfies exact aggregability. The price indices $a(p)$, $b(p)$, and $c(p)$ are defined in the following manner:

$a(p) \equiv a_0 + \alpha^T p + \frac{1}{2} p^T \Gamma p, b(p) \equiv \exp\left(\beta^T p\right)$, and $c(p) \equiv \lambda^T p$,

where $\alpha = (\alpha^1, \ldots, \alpha^N)^T$, $\beta = \left(\beta^1, \ldots, \beta^N\right)^T$, $\lambda = \left(\lambda^1, \ldots, \lambda^N\right)^T$, and $\Gamma = (\gamma^{n_1, n_2})_{1 \le n_1, n_2 \le N}$. We set a_0 to be the observed minimum value of m following Deaton and Muellbauer (1980) and Banks et al. (1997). Applying these definitions and Roy's identity in Eq. (5), we have the following column N-vector of expenditure share functions $w = (w^1, \ldots, w^N)^T$:

$$w = \alpha + \beta(m - a(p)) + \frac{\lambda}{b(p)}(m - a(p))^2 + \Gamma p. \tag{6}$$

Because the expenditure shares add up to one when summed across all the goods,

w has to satisfy $w^T \mathbf{1}_N = 1$ for all p, where $\mathbf{1}_N$ is column N-vectors of ones. Therefore, this adding-up constraint requires the following restrictions on α, β, λ, and Γ:

$$\alpha^T 1_N = 1, \beta^T 1_N = \lambda^T 1_N = 0, \text{ and } \Gamma^T 1_N = 0_N.$$

Since all of these constraints are linear in the parameters, we can impose the constraints simply by eliminating the redundant parameters from the equations. That is, we can rewrite the adding-up constraints as follows:

$$\alpha^N = 1 - \sum_{n=1}^{N-1} \alpha^n, \beta^N = -\sum_{n=1}^{N-1} \beta^n, \lambda^N = -\sum_{n=1}^{N-1} \lambda^n, \text{ and } \gamma^{N,n} = -\sum_{m=1}^{N-1} \gamma^{m,n} \quad \text{for } n \in \{1, \ldots, N\}.$$

With these constraints, the Nth equation in Eq. (6) is trivially satisfied. Thus, we can simply drop the Nth equation to arrive at a system of $K(=N-1)$ estimation equations. Furthermore, note that symmetry of the Slutsky matrix requires $\Gamma = \Gamma^T$. Therefore, together with the adding-up constraint, we must have

$$\gamma^{n,N} = -\sum_{m=1}^{N-1} \gamma^{n,m} \text{ for } n \in \{1, \ldots, N\}.$$

Using this, we can rewrite the system of equations in Eq. (6) with the Nth component dropped. To this end, we denote w, α, β, λ, and γ with their Nth component dropped by $\widetilde{w}$, $\widetilde{\alpha}$, $\widetilde{\beta}$, $\widetilde{\lambda}$, and $\widetilde{\gamma}$. Similarly, we denote Γ with its last row and column dropped by $\widetilde{\Gamma}$. We further define $\widetilde{p}$ to be a K-vector of (normalized) prices, whose kth element is $p^k - p^N$, and also define $\widetilde{a}_0 \equiv a_0 + p^N$. Then, we can rewrite the system of estimation equations as follows:

$$\widetilde{w} = \widetilde{\alpha} + \widetilde{\beta}(m - \widetilde{a}(\widetilde{p})) + \frac{\widetilde{\lambda}}{\widetilde{b}(\widetilde{p})}(m - \widetilde{a}(\widetilde{p}))^2 + \widetilde{\Gamma}\widetilde{p},$$

where $\widetilde{a}(\widetilde{p})$ and $\widetilde{b}(\widetilde{p})$ are defined as follows:

$$\widetilde{a}(\widetilde{p}) \equiv \widetilde{a}_0 + \widetilde{\alpha}^T \widetilde{p} + \frac{1}{2} \widetilde{p}^T \widetilde{\Gamma} \widetilde{p} \text{ and } \widetilde{b}(\widetilde{p}) \equiv \exp\left(\widetilde{\beta}^T \widetilde{p}\right).$$

The symmetry constraint for the estimation of QUAIDS models is often not imposed when running regressions, as is the case with Blundell and Robin (1999), but by the minimum chi-square distance estimator. As Blundell (1988) and Browning and Meghir (1991) argue, this approach has an advantage that the resulting chi-squared statistic can be used to test the symmetry. However, the minimum chi-square distance estimator requires accurate estimation of the variance–covariance matrix of the unrestricted estimator. This can be problematic in a finite sample when the number of goods in the economy is large. This is an important issue especially because the strength of the ILLS estimator is in its ability to estimate large demand systems.

Therefore, we directly impose the symmetry constraint by suitably transforming the problem. We note that the symmetry and adding-up constraints imply that there are $L \equiv K(K+1)/2$ free parameters in Γ. With a slight abuse of notation, we write these free parameters by $\gamma^l = \gamma^{k_1,k_2}\left(= \gamma^{k_2,k_1}\right)$ for $l = (k_1 - 1)k_1/2 + k_2$ with $1 \le k_1 \le k_2 \le K$. It is also convenient to define the mapping from l to the corresponding pair of indices. That is, we have $\gamma^l = \gamma^{i_1(l),i_2(l)}$ for all l by defining

$$i_1(l) = \max_{i \in \mathbf{N}}\left\{ i \middle| \frac{(i-1)i}{2} < l \right\} \text{ and } i_2(l) = l - \frac{\left(i_1(l) - 1\right)i_1\left(l\right)}{2}.$$

To apply the IGLLS estimator in the estimation of a QUAIDS, it is useful to define a few matrices. Let us define

$$A_h^1 \equiv (m_h - \widetilde{a}(\widetilde{p}_h))I_K \text{ and } A_h^2 \equiv \frac{(m_h - \widetilde{a}(\widetilde{p}_h))^2}{\widetilde{b}(\widetilde{p}_h)} I_K,$$

where I_K is a $K \times K$-identity matrix and the subscript h denotes a household. Furthermore, let us define a $K \times L$-matrix A_h^3, whose (k, l) element is $k = i_2(l)$ if $k = i_2(l)$, $\widetilde{p}_h^{i_2(l)}$ if $k = i_1(l)$, and zero otherwise. Using these notations, we can write the system of estimation equations as follows:

$$\widetilde{w}_h = g(x_h, \theta)\theta + u_h$$

where the set of parameters to estimate is $\theta = \left[\alpha^1, \ldots, \alpha^K, \beta^1, \ldots, \beta^K, \gamma^1, \ldots, \gamma^L\right]^T$, the observable characteristics are $x_h = (m_h, \widetilde{p}_h)$, and $g(x_h, \theta) = \left[I_K, A_h^1, A_h^2, A_h^3\right]$. Note that θ is unconstrained, because both the adding-up and symmetry constraints have already been internalized.

So far, we have ignored the potential heterogeneity in demand across different households with different demographic groups. To address this issue, we also include a few demographic variables such as the household size, the gender of the household head, and the educational attainment of the household head using the method adopted by Abdulai (2002), which adjusts the intercept term a_0 by the demographic characteristics of the household.

To estimate the variance–covariance matrix for the IGLLS estimator, it is necessary to find $h(x_h, \theta)$ defined in Theorem 1. To this end, we define π to be an L-vector of quadratic logarithmic prices whose L-th element is $p^{i_1(l)}p^{i_2(l)}$ if $i_1(l) = i_2(l)$ and $2p^{i_1(l)}p^{i_2(l)}$ if $i_1(l) \neq i_2(l)$. Using this, it can be shown that $h(x_h, \theta)$ can be written as $h(x_h, \theta) = \left[B_h^1, B_h^2, O_K, B_h^3\right]$, where O_K is a $K \times K$-matrix of zeros and B_h^1, B_h^2, and B_h^3 are defined as follows:

$$B_h^1 = -\left(\widetilde{\beta} + \frac{2(m-a)}{b}\widetilde{\lambda}\right)\widetilde{p}^T, B_h^2 = -\frac{(m-a)^2}{b}\widetilde{\lambda}\widetilde{p}^T, \text{and } B_h^3$$
$$= -\left(\frac{\widetilde{\beta}}{2} + \frac{(m-a)}{b}\widetilde{\lambda}\right)\pi^T.$$

It is convenient to present the results in terms of the elasticity. The budget elasticities ξ_h^k and uncompensated price elasticities $\rho_h^{k_1,k_2}$ for household h are given by the equations

$$\begin{cases} \xi_h^k = \dfrac{1}{w_h^k}\left(\beta^k + \dfrac{2\lambda^k(m_h - a(p_h))}{b(p_h)}\right) + 1 \\ \rho_h^{k_1,k_2} = \dfrac{1}{w_h^k}\left(\gamma^{k_1,k_2} - \dfrac{\lambda^{k_1}\beta^{k_2}(m_h - a(p_h))^2}{b(p_h)}\right) - \left(\xi^{k_1} - 1\right)\left(\alpha^{k_2} + \sum_n \gamma^{k_2,n} p^n\right) - \delta_{k_1 k_2}, \end{cases} \tag{7}$$

where $\delta_{k_1k_2}$ is the Kronecker delta. We aggregate the elasticities found in this way by taking the weighted average with the weights being equal to the household's share of the total sample expenditure for the good of interest.

4 Data

For our empirical application, we combine FIES data with the annual Consumer Price Index (CPI) data, both of which are collected by the National Statistics Office (NSO) of the Philippines. The FIES contains detailed questions on consumption and expenditure as well as some other characteristics of the household. We focus on urban single-family households headed by a married working-age person with at least one child and no more than seven children to have reasonably homogeneous household composition. We use six rounds of the FIES data in 1998, 1991, 1994, 2000, 2003, and 2006 for this study, which contain 4584, 7577, 7262, 10270, 8652, and 7289 households, respectively.

The CPI data are based in year 2000 and available at the provincial level or lower for an overwhelming majority of the FIES households.[1] For a small fraction of FIES households where the CPI data are not available at the provincial level, we use the

[1] There are about 80 provinces in the Philippines during the study period, though the definitions of provinces change slightly over time. We use the finest geographic disaggregation that is possible in the data.

regional CPI data for the survey year. To use the differences in the price changes across provinces over time, we divide the data into pre-1997 period (i.e., 1988, 1991, and 1994) and post-1997 period (i.e., 2000, 2003, and 2006).

In this study, we only take the urban sample in the FIES data set. This choice is driven by two considerations. First, the CPI data are mainly collected in urban areas. Therefore, CPI may not capture very well the actual price system that rural households face. Second, most studies on food demand in China we are aware of are focused on urban areas. Therefore, to facilitate the cross-country comparisons between China and the Philippines, it is sensible to use only the urban data.

Because the definition of goods between the FIES and CPI are not the same, we have aggregated both data across goods so that the definitions of goods in the two data sets match.[2] As a result of this aggregation, we have the price and expenditure share for each household and for each of the 19 items of goods (expenditure categories), which include seven food items and 12 non-food items. Table 1 shows the definition of the 19 expenditure categories as well as their expenditure share in 1988 and 2006 disaggregated by the per capita expenditure quintile of the household, where Q1 represents the top (richest) quintile and Q5 the bottom (poorest) quintile. The reported figure in each cell is calculated as the average share for each item and quintile weighted by the product of the household's total expenditure and the household's sample weight.

As can be seen from Table 1, there are some consistent patterns that are observed over the study period. For example, the share of cereal (item #1) expenditure is lower for richer quintiles, a finding that is expected from previous studies. Table 1 also shows that there is some heterogeneity in the relationship between expenditure share for non-food items and total expenditure quintile. For example, richer households tend to allocate a higher share of expenditure on the rental of dwelling unit (item #11), transportation and recreation (item #16), communication (item #17), and household furnishing and equipment (item #18). However, there is no such relationship for fuel, light, and water (item #12), and only a weak relationship is observed for medical care (item #14) and personal care and household operation (item #15).

Table 1 is also consistent with the westernization of Filipino diet during the study period. While the expenditure shares for major food items have declined, the relative declines are different across food items. Therefore, the relative importance of dairy and eggs (item #2) and meat (item #5) within the food budget has increased over time. On the other hand, cereals (item #1), the most important food category in the traditional Filipino diet, have witnessed the largest absolute decline in the expenditure share during our study period.

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[2] Apparently, Mutuc et al. (2007) have used FIES data for the year 2000, which contain the expenditure and quantity for each food item. However, the data we purchased from the NSO only contain the expenditure data, and thus we cannot derive the implicit prices households face from the FIES data. Furthermore, it would not be possible to obtain relevant quantities for non-food items. Therefore, we chose to aggregate goods instead in this study.

Table 1 Expenditure shares in percentage by expenditure items and per capita expenditure quintiles for 1988 and 2006

Item #	Description	1988						2006					
		Q1	Q2	Q3	Q4	Q5	Total	Q1	Q2	Q3	Q4	Q5	Total
1	Cereals	7.8	13.0	16.5	21.5	29.0	13.3	5.7	9.7	12.9	17.3	25.1	10.2
2	Dairy and eggs	4.3	5.0	4.7	4.3	3.3	4.4	3.6	4.2	3.9	3.7	3.2	3.7
3	Fish and seafood	4.7	7.0	8.6	10.3	11.4	6.9	3.3	5.1	6.2	7.5	9.5	5.0
4	Fruits and vegetables	4.9	6.1	6.3	6.1	6.7	5.6	3.4	4.5	5.1	5.6	6.2	4.3
5	Meat	9.1	8.6	7.7	5.7	4.6	8.1	6.7	8.4	8.5	7.6	5.9	7.4
6	Miscellaneous food	9.4	12.2	12.6	11.3	9.6	10.8	11.1	13.4	14.8	13.9	11.7	12.5
7	Beverages (incl. alcohol)	2.5	2.9	2.9	2.9	2.3	2.7	2.1	2.6	2.7	2.7	2.4	2.4
8	Tobacco	1.4	2.1	2.7	2.8	2.5	2.0	0.4	0.9	1.3	1.5	1.6	0.9
9	Clothes	4.4	4.4	4.2	4.3	3.7	4.3	2.9	2.6	2.3	2.2	2.0	2.6
10	Housing maintenance and repair	1.3	0.6	0.7	0.6	0.7	0.9	0.6	0.4	0.4	0.3	0.3	0.5
11	Rental of occupying dwelling	18.4	13.3	11.1	9.6	7.9	14.4	15.6	13.6	11.9	10.9	8.7	13.7
12	Fuel, light, and water	5.2	5.9	5.5	6.0	6.1	5.5	8.1	9.0	8.9	8.5	7.8	8.4
13	Education	4.3	2.9	2.3	1.9	1.5	3.2	7.0	4.1	2.3	2.0	1.8	4.8
14	Medical care	2.1	1.4	1.1	1.2	1.1	1.6	2.9	1.9	1.5	1.3	1.3	2.2
15	Personal care and HH operation	7.1	5.8	5.7	5.5	5.4	6.3	7.3	6.1	6.1	6.1	6.1	6.6
16	Recreation	0.8	0.5	0.4	0.3	0.2	0.6	0.9	0.4	0.3	0.2	0.2	0.6
17	Transportation and communication	6.7	4.3	4.0	3.3	2.4	5.1	11.1	8.4	7.6	5.9	4.3	9.0
18	HH furnishing and equipments	3.1	1.9	1.3	0.9	0.4	2.1	4.6	2.3	1.5	1.2	0.6	3.0
19	Other non-food items	2.4	2.1	1.8	1.4	1.1	2.0	2.7	2.3	1.9	1.5	1.2	2.3
Total		100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Number of observations		1035	953	903	881	812	4584	1637	1528	1397	1369	1358	7289

Source: Author's calculation based on the FIES sample used in this study

Table 2 Household characteristics by per capita expenditure quintiles for 1988 and 2006

Variable	Description	1988						2006					
		Q1	Q2	Q3	Q4	Q5	Total	Q1	Q2	Q3	Q4	Q5	Total
HHSIZE	Household size	4.8	5.1	5.5	5.9	6.6	5.5	4.3	4.6	5.2	5.7	6.3	5.1
HHPRI	Head has at least some primary educ (%)	98.1	94.9	90.6	80.6	70.5	88.1	98.2	95.8	91.6	84.0	70.6	89.4
HHSEC	Head has at least some secondary educ (%)	86.5	67.0	50.0	35.7	24.7	55.2	91.2	77.7	62.1	45.7	26.8	63.8
HHCOL	Head has at least some college educ (%)	61.4	33.6	21.1	14.0	7.9	29.6	66.5	37.1	23.7	14.1	7.6	32.6
HHFEM	Female headed household (%)	12.7	6.1	3.3	2.6	2.3	5.8	18.0	7.2	3.5	2.9	2.1	7.5
HHAGE	Head's age	39.3	39.0	38.5	39.0	39.0	39.0	40.9	39.5	39.3	40.3	40.5	40.1

Source: Author's calculation based on FIES data

Table 2 describes the household characteristic variables used in this study. The reported figures are the mean within each quintile weighted by the sample weight. The first row (HHSIZE) shows that poor quintiles tend to have a larger household and that the household size has declined for all the quintiles over the study period. The second, third, and fourth rows show that the household heads in richer quintiles tend to be better educated than those in poorer quintiles. Note that those who have at least some secondary (college) education are automatically deemed to have at least some primary (secondary) education. Therefore, HHSEC (HHCOL) is by definition no larger than HHPRI (HHSEC) for all quintiles. The fourth row shows that the top quintile is disproportionately represented by female headed households. We find no obvious difference in head's age across different quintiles.

5 Results

We estimate the QUAIDS for the 19 items using the IGLLS estimator presented in Sect. 3 for 1988–1994 and 2000–2006 periods separately. In all the regressions, we control for the region and year. Table 3 reports the estimated coefficients on demographic shifters and their statistical significance. For example, it shows that the expenditure share for cereals tends to increase by 1.71 and 1.53 % points, respectively, for the periods of 1988–1994 and 2000–2006 when the household has one additional member, after controlling for a variety of other factors.

Table 3 also shows that better educated households tended to spend a higher share of expenditure on major protein sources including dairy and eggs (item #2), fish and seafood (item #3), and meat (item #5) for the 1988–1994 period, even after controlling for a variety of other factors including the total budget. While this pattern still exists for the 2000–2006 period, the gap between educated and non-educated households appear to have narrowed slightly.

Tables 4 and 5, respectively, present the total budget elasticities and uncompensated own-price elasticities for food items based on Eq. (7) as well as their changes over time and the statistical significance of the changes due to the independent test of equality. To obtain these estimates taking account of both the model and sampling errors, we randomly draw the parameters from a normal distribution with the estimated asymptotic mean and variance for 1000 rounds of simulation and impute the elasticities for each household for a bootstrapped sample in each round. We then aggregate over each quintile and obtain an estimate for each round. Taking the mean and standard deviation of these estimates over all the rounds, we have the estimated point estimates and their standard errors.

Table 4 shows that the budget elasticity is smaller for richer quintiles for all food items. The table also shows that the budget elasticity has generally declined over time. This is not surprising given the economic growth that has taken place over the study period. The only exception is cereals (item #1) for the top quintile, which is also not so surprising because households in the top quintile are already able to fully

Table 3 The estimated QUAIDS coefficients on demographic variables

	HHSIZE		HHPRI		HHSEC		HHCOL		HHFEM		HHAGE	
Item #	1988–1994	2000–2006	1988–1994	2000–2006	1988–1994	2000–2006	1988–1994	2000–2006	1988–1994	2000–2006	1988–1994	2000–2006
1	1.71^{***}	1.53^{***}	-1.03^{***}	-1.09^{***}	-1.03^{***}	-0.62^{***}	-0.38^{***}	-0.28^{***}	0.61^{***}	0.32^{***}	0.07^{***}	0.05^{***}
2	2.68^{***}	0.86^{***}	0.82^{***}	0.48^{**}	0.86^{***}	0.22^{*}	0.65^{***}	0.46^{***}	2.97^{***}	1.93^{***}	3.36^{***}	3.16^{***}
3	3.01^{***}	1.32^{***}	4.07^{***}	4.07^{***}	3.67^{***}	2.73^{***}	4.19^{***}	2.85^{***}	1.30^{***}	1.56^{***}	2.23^{***}	3.52^{***}
4	2.28^{***}	1.18^{***}	3.41^{***}	4.63^{***}	3.73^{***}	3.48^{***}	3.46^{***}	3.08^{***}	0.13	-1.59^{***}	0.87^{***}	-1.38^{***}
5	-0.06^{***}	-0.07^{***}	0.39^{***}	0.18^{***}	0.25^{***}	0.27^{***}	0.30^{***}	0.22^{***}	-0.23^{**}	−0.04	-0.09^{***}	-0.09^{***}
6	$-0\ 49^{***}$	0.05	−0.19	−0.10	−0.01	0.17^{*}	−0.16	-0.24^{***}	−0.09	−0.04	-0.48^{***}	-0.19^{*}
7	-0.59^{***}	0.01	−0.22	−0.13	−0.08	0.11	−0.16	0.31^{***}	-0.57^{***}	0.01	-0.42^{***}	−0.02
8	−0.23	−0.11	-0.37^{**}	-0.38^{***}	-0.71^{***}	0.09	−0.20	-0.43^{***}	0.17	0.34^{***}	−0.23	−0.07
9	0.16^{***}	0.23^{***}	-0.60^{***}	-0.57^{***}	-0.76^{***}	-0.48^{***}	-0.71^{***}	-0.45^{***}	-0.62^{***}	-0.50^{***}	-0.01^{**}	0.01^{***}
10	-0.52^{***}	-0.51^{***}	-1.06^{***}	0.91^{***}	−0.13	-0.25^{***}	0.95^{***}	0.03	3.38^{***}	1.80^{***}	1.68^{***}	0.63^{***}
11	2.89^{***}	2.42^{***}	3.81^{***}	2.15^{***}	2.33^{***}	2.62^{***}	0.90^{***}	0.63^{***}	1.59^{***}	1.14^{***}	0.46^{**}	-0.37^{***}
12	-1.66^{***}	−0.13	1.13^{***}	0.31^{**}	3.44^{***}	1.07^{***}	0.99^{***}	-0.24^{*}	−0.04	-0.47^{***}	0.08	−0.11
13	0.02	0.04^{***}	-0.39^{***}	-0.34^{***}	-0.15^{**}	−0.06	-0.15^{**}	-0.24^{***}	−0.15	−0.03	0.00	0.00
14	$-0\ 44^{***}$	0.40^{***}	1.50^{***}	0.81^{***}	-0.19^{**}	-0.91^{***}	-0.71^{***}	-1.00^{***}	-0.85^{***}	−0.13	-1.64^{***}	-1.12^{***}
15	-148^{***}	-1.62^{***}	-0.85^{***}	-1.20^{***}	-0.30^{*}	-0.49^{***}	-0.50^{***}	-1.27^{***}	−0.03	-0.65^{***}	0.05	-0.30^{***}
16	1.21^{***}	0.84^{***}	−0.24	1.12^{***}	-0.31^{**}	-0.56^{***}	-0.95^{***}	-0.32^{***}	0.21^{**}	0.14^{**}	-0.91^{***}	-0.49^{***}
17	-0.26^{***}	-0.13^{***}	0.42^{***}	0.32^{***}	0.34^{***}	0.31^{***}	0.12	-0.22^{***}	0.22	−0.17	-0.02^{***}	-0.03^{***}
18	-1.47^{***}	0.92^{***}	0.08	0.95^{***}	0.41^{***}	0.53^{***}	-0.49^{***}	−0.16	-3.40^{***}	-2.25^{***}	-3.45^{***}	-2.74^{***}
19	-1.99^{***}	-1.37^{***}	-184^{***}	-2.20^{***}	-3.78^{***}	-2.91^{***}	-2.39^{***}	-1.77^{***}	-1.95^{***}	-1.15^{***}	-1.67^{***}	-3.02^{***}

Note: Author's calculation based on FIES and CPI data. Statistical significance at 10, 5, and 1 % levels is indicated by *, **, and ***, respectively. All coefficients are expressed in percentage

Table 4 Budget elasticities of demand for food items

Item #	Year	Q1		Q2		Q3		Q4		Q5		Total	
1	1988	0.040	(0.017)	0.189	(0.011)	0.293	(0.010)	0.407	(0.008)	0.514	(0.007)	0.259	(0.008)
	2006	0.085	(0.021)	0.132	(0.011)	0.253	(0.008)	0.374	(0.007)	0.497	(0.006)	0.245	(0.008)
	Diff	0.045		−0.057***		−0.040***		−0.033***		−0.017*		−0.013	
2	1988	0.856	(0.015)	1.062	(0.009)	1.140	(0.012)	1.225	(0.015)	1.376	(0.024)	1.020	(0.011)
	2006	0.716	(0.023)	0.940	(0.010)	1.009	(0.010)	1.087	(0.013)	1.225	(0.020)	0.885	(0.013)
	Diff	−0.140***		−0.123***		−0.131***		−0.138***		−0.151***		−0.135***	
3	1988	0.517	(0.019)	0.684	(0.011)	0.744	(0.010)	0.791	(0.010)	0.814	(0.010)	0.677	(0.010)
	2006	0.356	(0.025)	0.513	(0.011)	0.575	(0.009)	0.630	(0.009)	0.684	(0.009)	0.518	(0.011)
	Diff	−0.161***		−0.172***		−0.169***		−0.161***		−0.129***		−0.159***	
4	1988	0.727	(0.012)	0.802	(0.008)	0.814	(0.009)	0.817	(0.010)	0.841	(0.011)	0.781	(0.008)
	2006	0.551	(0.019)	0.682	(0.009)	0.721	(0.008)	0.754	(0.008)	0.785	(0.010)	0.661	(0.010)
	Diff	−0.176***		−0.121***		−0.093***		−0.063***		−0.056***		−0.119***	
5	1988	1.032	(0.010)	1.193	(0.008)	1.278	(0.011)	1.453	(0.018)	1.663	(0.029)	1.164	(0.009)
	2006	0.668	(0.018)	0.997	(0.007)	1.095	(0.007)	1.214	(0.010)	1.473	(0.018)	0.927	(0.010)
	Diff	−0.364***		−0.195***		−0.183***		−0.239***		−0.189***		−0.237***	
6	1988	0.868	(0.013)	1.032	(0.007)	1.078	(0.008)	1.139	(0.010)	1.238	(0.015)	1.002	(0.008)
	2006	0.764	(0.014)	0.920	(0.006)	0.967	(0.005)	1.007	(0.006)	1.081	(0.011)	0.885	(0.008)
	Diff	−0.105***		−0.112***		−0.111***		−0.132***		−0.157***		−0.116***	
7	1988	1.005	(0.017)	1.230	(0.013)	1.296	(0.014)	1.378	(0.019)	1.536	(0.026)	1.183	(0.013)
	2006	0.705	(0.024)	1.012	(0.010)	1.101	(0.010)	1.187	(0.011)	1.344	(0.019)	0.949	(0.013)
	Diff	−0.300***		−0.218***		−0.195***		−0.191***		−0.192***		−0.234***	

Note: Author's calculation based on FIES data. Standard errors are in parentheses. Statistical significance at 10, 5, and 1 % levels is indicated by *, **, and ***, respectively

Table 5 Uncompensated own-price elasticities of demand for food items

Item #	Year	Q1		Q2		Q3		Q4		Q5		Total	
1	1988	0.550	(0.094)	−0.158	(0.053)	−0.352	(0.041)	−0.510	(0.031)	−0.639	(0.023)	−0.146	(0.052)
	2006	0.736	(0.167)	−0.054	(0.096)	−0.296	(0.072)	−0.479	(0.053)	−0.637	(0.037)	−0.070	(0.092)
	Diff	0.186		0.104		0.056		0.032		0.002		0.076	
2	1988	−1.016	(0.091)	−1.048	(0.077)	−1.063	(0.082)	−1.078	(0.088)	−1.107	(0.106)	−1.043	(0.087)
	2006	−0.993	(0.143)	−1.016	(0.122)	−1.025	(0.130)	−1.035	(0.139)	−1.050	(0.156)	−1.011	(0.136)
	Diff	0.022		0.032		0.038		0.044		0.057		0.032	
3	1988	−1.177	(0.069)	−1.120	(0.046)	−1.099	(0.038)	−1.082	(0.031)	−1.074	(0.028)	−1.122	(0.047)
	2006	−1.238	(0.130)	−1.151	(0.083)	−1.124	(0.068)	−1.102	(0.057)	−1.079	(0.045)	−1.155	(0.085)
	Diff	−0.061		−0.031		−0.025		−0.020		−0.005		−0.033	
4	1988	−1.005	(0.039)	−1.005	(0.031)	−1.006	(0.030)	−1.006	(0.031)	−1.006	(0.028)	−1.005	(0.033)
	2006	−0.673	(0.076)	−0.755	(0.057)	−0.781	(0.051)	−0.802	(0.046)	−0.822	(0.042)	−0.743	(0.060)
	Diff	0.331***		0.250***		0.224***		0.204***		0.184***		0.262***	
5	1988	−0.838	(0.070)	−0.872	(0.074)	−0.872	(0.082)	−0.846	(0.108)	−0.836	(0.130)	−0.852	(0.078)
	2006	−1.233	(0.101)	−1.248	(0.081)	−1.266	(0.080)	−1.315	(0.090)	−1.432	(0.114)	−1.262	(0.092)
	Diff	−0.395***		−0.376***		−0.394***		−0.469***		−0.596***		−0.410***	
6	1988	−0.872	(0.059)	−0.944	(0.045)	−0.959	(0.043)	−0.966	(0.048)	−0.976	(0.057)	−0.923	(0.051)
	2006	−0.950	(0.066)	−0.983	(0.055)	−0.992	(0.050)	−0.999	(0.053)	−1.010	(0.063)	−0.975	(0.059)
	Diff	−0.078		−0.040		−0.034		−0.033		−0.034		−0.052	
7	1988	−1.321	(0.100)	−1.304	(0.086)	−1.295	(0.081)	−1.306	(0.083)	−1.359	(0.095)	−1.313	(0.091)
	2006	−0.627	(0.179)	−0.725	(0.142)	−0.740	(0.137)	−0.750	(0.135)	−0.734	(0.148)	−0.693	(0.155)
	Diff	0.694***		0.580***		0.555***		0.556***		0.625***		0.620***	

Note: Author's calculation based on FIES data. Standard errors are in parentheses. Statistical significance at 10, 5, and 1 % levels is indicated by *, **, and ***, respectively satisfy their basic needs and cereals are, therefore, budget inelastic. This pattern did not change over time.

Table 5 shows that the uncompensated own-price elasticities are strikingly similar across quintiles for all the food items except for cereals (item #1). Cereals are clearly inferior goods for the top quintile, but it is a normal good for poorer quintiles. Table 5 also shows that there has been a statistically and economically significant decline in the magnitude of elasticity for fruits and vegetables (item #4) and beverages (item #7), whereas there has been a significant increase for meat (item #5). Both Tables 4 and 5 strongly indicate the presence of structural change between 1988 and 2006 as has been found in studies in China.

While our results cannot be directly compared with the studies on food demand in China because of the difference in the definition of food items, coverage of time periods, and the methodology used to derive elasticities, there are some common patterns observed in the changes in food demand between the two countries. First, increases in the magnitude of uncompensated own-price elasticity for meat have been observed in several studies in China. For example, Hovhannisyan and Gould (2014) report that the meat price elasticity has changed from −0.618 to −0.978 in their study period between 2002 and 2010. For earlier periods, Hovhannisyan and Gould (2011) estimate uncompensated own-price elasticities for beef, pork, and poultry for 1995 and 2003. The elasticities for pork and poultry have increased substantially, whereas that for beef slightly declined.

Second, as with our study, Hovhannisyan and Gould (2011) also find that the uncompensated own-price elasticities for vegetables and fruits have declined in their magnitudes between 1995 and 2003 (−0.520 to −0.457 for vegetables and −0.923 to −0.699 for fruits). For the period between 2002 and 2010, Hovhannisyan and Gould (2014) indicate that vegetables have become less elastic whereas fruits have become only slightly more elastic. Finally, Hovhannisyan and Gould (2011) find that the budget elasticity of demand has declined for a majority of food items they studied, which is similar to what we find.

6 Discussion

In this paper, we have estimated QUAIDS over a long period of time using a consistent methodology. While we have focused on the food demand, we chose to estimate the whole demand system to avoid assuming separability and excessively aggregating non-food items. However, this necessitates the estimation of a large demand system, which involves a large number of parameters. This issue becomes even more serious when some key demographic variables are included in the regression as they inflate the number of parameters to be estimated. To address these issues, we exploit the conditional linearity of the QUAIDS and developed and applied the IGLLS estimator.

Using six rounds of the FIES data, we have estimated a QUAIDS with 19 goods. We find that the urban Filipino diet is getting more westernized and that the food demand in the Philippines has structurally changed during our study period between 1988 and 2006. In particular, the changes in demand for meat, vegetables, and fruits in the urban Philippines have been qualitatively similar to those observed in China.

The estimation results presented in this study have some policy implications. For example, as we have seen in the case of recent food inflation, the prices also affect poverty heterogeneously across households (Fujii 2013). Therefore, how food demand changes according to the changes in prices and incomes and how it varies across households are crucial for the assessment and formulation of economic policies, including agricultural subsidies, taxes, infrastructure investment, and social protection.

Our results also have some business implications. In general, if markets are segmented and people in different budget quintiles respond differently to price or total budget changes, then separate marketing and pricing strategies may be needed for different per capita expenditure quintiles. As we can see from Tables 4 and 5, there is a marked difference across quintiles for the demand of cereals (item #1). However, the price elasticities for other major food items including dairy and eggs (item #2), fish and seafood (item #3), fruits and vegetables (item #4), and meat (item #5) are rather similar across quintiles. Therefore, we do not have evidence to suggest that separate pricing strategies are needed for these items in the Philippines.

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