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HOGLEX Demand Systems and Welfare Policy in Major ASEAN Developing Countries: A Bayesian Analysis Using Expenditure Unit Records

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Abstract

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Keywords

HOGLEX, Demand, Systems, Welfare, Policy, Major, ASEAN, Developing, Countries, Bayesian, Analysis, Using, Expenditure, Unit, Records

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HOGLEX Demand Systems and Welfare Policy in Major ASEAN Developing Countries: A Bayesian Analysis Using Expenditure Unit Records*

Hikaru Hasegawa, Tran Van Hoa and Rebecca Valenzuela

8.1 Introduction

The explicit and estimable HOGLEX demand system (Tran Van Hoa, 1983, 1985 and Jerison and Jerison, 1984) links for the first time an important aspect of economic theory and the statistical Box-Cox transformation analysis. This demand system from the point of view of consistent aggregation and preference theory is well known as the PIGL (Price Independent Generalized Linearity) presented by Muellbauer (1975). The HOGLEX system is economic-theoretically integrable and flexible in the sense that it is derived from utility maximization and encompasses most other well-known utility-based demand systems in the literature on consumer behaviour (Laitinen *et al.*, 1983). From an application perspective, the HOGLEX system is more realistic in that the functional form of its demand equations is specific-data-based and does not require a priori an approximate and, probably, inappropriate specification. The danger of using an inappropriate functional form of demand for a particular dataset for practical policy analysis has been pointed out by many previous investigators in the area, including Prais and Houthakker in the 1950s and Leser in the 1960s.

The Engel version of the HOGLEX demand system of M commodities can be defined for our study below as:

$$w_i = \alpha_i + \beta_i y^{-\lambda}, \quad i = 1, \dots, M, \quad (1)$$

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where w_i is a budget share of the i th commodity and y is total expenditure and used as income. Imposing the adding-up condition, we have $\sum_{i=1}^M \alpha_i = 1$ and $\sum_{i=1}^M \beta_i = 0$. Therefore, when we estimate the model under this condition of degeneracy, the number of equations reduces to $m = M - 1$.

Empirical studies of the HOGLEX demand systems to date have been based on conventional OLS or MLE estimation methods using time-series or panel aggregate data (see however Tran Van Hoa, 1985), and their policy implications, if any, have been based on these OLS or MLE estimates. This chapter departs significantly from this approach in four novel aspects. First, we estimate the HOGLEX system from a Bayesian approach and, for convenient comparative purposes with previous related studies, we restrict ourselves to three HOGLEX subsets, well known and often used in empirical modelling and analysis in this area. That is,

$$w_i = \alpha_i + \beta_i \log y, \quad \lambda = 0 \quad (\text{AIDS}),$$

$$w_i = \alpha_i + \beta_i \frac{1}{y}, \quad \lambda = 1 \quad (\text{LINEX}),$$

$$w_i = \alpha_i + \beta_i y, \quad \lambda = -1 \quad (\text{RECIPROCAL}).$$

Second, the chapter emphasizes the relevance of our modelling, estimating approach and findings to practical welfare policy analysis at the fairly disaggregated level for different socio-demographic groups for possible use especially in developing economies. This is done through the use of household expenditure survey (HES) microdata or unit records from two major ASEAN countries (that is, Thailand and the Philippines) in the estimation of these subsets and for a number of important socio-demographic cohorts. The technical selection of the best empirical Engel models for this dataset is then based on the Bayes factor. It is important to note that since the value of λ in the HOGLEX model above represents the effects of the shape of income (total expenditure) distribution on budget shares for every cohort (see Deaton and Muellbauer, 1980, pp. 154-158) and Tran Van Hoa, 1985), the selected estimated models capture these effects and use them in calculating average incomes for different cohorts. These incomes form the basis for formulating and implementing social security policy and other related issues in welfare economics with applications to both developed and developing countries.

Third, since 'dirty' or incorrectly chosen or available data are the norm in empirical studies of this kind, their presence may bias or distort the resulting estimated findings and subsequent policy implications to some significant extent. To deal with this problem, we introduce the effect of so-called measurement errors in total expenditure into our HOGLEX models for Bayesian analysis. In the non-Bayesian literature, for example Hausman, Newey and Powell (1995) consider the

errors-in-variables (EIV) problem in the estimation of Engel curves. Lewbel (1996) deals with expenditure measurement errors on the left and right hand sides of the demand equations and estimates them using a GMM estimator. In a classical or non-Bayesian estimation of the demand models subject to measurement errors, instrumental variables are frequently used. However, in a Bayesian analysis, they are not necessary (see, for example, Mallick and Gelfand, 1996, p. 311). In our study, we propose to use the simulation-based approach (that is, Markov Chain Monte Carlo (MCMC) methods), and implement in a simple way the Bayesian estimation of the EIV specification (see, for example, Hasegawa and Kozumi, 2001, of the Engel curves using this approach). Finally, it is important to note that empirical studies in demand analysis have to date invariably made use of the concept of arithmetic (in the case of LINEX models) or weighted mean incomes in their calculation. The approach has necessarily assumed a perfectly democratic measurement of income (that is, where all consumers have equal weights to all levels of income in consumption) or zero Gini coefficient in income distribution, and crucially ignored the reality that consumers may have different preferences in consumption at different levels of income. As a contribution to this area of studies, our chapter points out a new approach to modelling consumer's behaviour in a multi-commodity framework capturing this impact of income distribution or inequality and incorporating it in deriving estimates and results more credible and useful to practical social security studies and welfare assessment.

The plan of this chapter is as follows. In Section 8.2, we formally describe the Bayesian framework for the Engel version of the HOGLEX demand models without and with measurement errors. In Section 8.3, we use the recent HES microdata of Thailand and the Philippines for five standard socio-demographic cohorts to estimate the three HOGLEX Engel subsets (that is, $\lambda = 0, 1, -1$) and compare the results for our dataset. We then obtain and compare the results of our estimated models and incomes in the cases of with and without measurement errors. Policy implications of our empirical findings for social security studies and welfare analysis and concluding remarks are briefly presented in Section 8.4.

8.2 Bayesian Framework

8.2.1 The HOGLEX Engel Model without Measurement Errors

We specify the exact HOGLEX Engel model (that is, without measurement errors) as follows:

$$w_h = \alpha + \beta y_h^{-\lambda} + u_h, \quad h = 1, \dots, H, \quad (2)$$

where h denotes the h th household, H is the number of households and

$$w_h = \begin{bmatrix} w_{1h} \\ \vdots \\ w_{mh} \end{bmatrix}, \alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_m \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix}, u_h = \begin{bmatrix} u_{1h} \\ \vdots \\ u_{mh} \end{bmatrix}.$$

In the model (2), when $\lambda \rightarrow 0$,

$$w_h = \alpha + \beta \log y_h + u_h, \quad h = 1, \dots, H.$$

We put $\gamma = \text{vec} B = \text{vec} \begin{bmatrix} \alpha' \\ \beta' \end{bmatrix}$ and the data $z_h = [w_h', y_h']$. We also assume $u_h \sim N(0, \Sigma)$, where Σ is an $m \times m$ covariance matrix, and u_h and u_j are independent for $h \neq j$.

We introduce the following prior information for γ and Σ^{-1} .

$$\gamma \sim N(\gamma_*, \Phi_*), \quad \Sigma^{-1} \sim W(G_*, \nu_*), \quad (3)$$

where $W(A, a)$ denotes a Wishart distribution with a covariance matrix A and degrees of freedom a .

We write the data set as $Z = \{z_1, \dots, z_H\}$ and the parameter set as $\theta = \{\gamma, \Sigma\}$. Let ' $\cdot | \dots$ ' denote conditioning on the values of all other parameters and data. Given the prior information (3) and the model (2), we can easily derive the following full conditional distributions (FCD) of γ and Σ^{-1} . The FCD of γ is

$$\gamma | \dots \sim N(\gamma_{**}, \Phi_{**}), \quad (4)$$

where

$$\Phi_{**} = (\Sigma^{-1} \otimes Y'Y + \Phi_*^{-1})^{-1},$$

$$\gamma_{**} = \Phi_{**} [\Phi_*^{-1} \gamma_* + (\Sigma^{-1} \otimes I_2) \text{vec}(Y'W)],$$

$$Y = \begin{bmatrix} 1 & y_1^{-\lambda} \\ \vdots & \vdots \\ 1 & y_H^{-\lambda} \end{bmatrix}, \quad W = \begin{bmatrix} w_1' \\ \vdots \\ w_H' \end{bmatrix}$$

and $\otimes$ denotes Kronecker product. The FCD of Σ^{-1} is

$$\Sigma^{-1} | \dots \sim W(G_{**}^{-1}, \nu_{**}), \quad (5)$$

where

$$G_{**} = (W - YB)'(W - YB) + G_*, \quad \nu_{**} = \nu_* + H.$$

8.2.2.2 The HOGLEX Engel Model with Measurement Errors

In this section, we introduce measurement errors into the regressors ($y_h^{-\lambda}$) of the HOGLEX Engel model. That is, we can only observe the true total expenditure (y_h^*) with errors as y_h . The HOGLEX Engel model with measurement errors can be written as

$$w_h = \alpha + \beta y_h^{*- \lambda} + u_h, \quad h = 1, \dots, H, \quad (6)$$

$$y_h = y_h^* + v_h, \quad h = 1, \dots, H, \quad (7)$$

where $v_h \sim N(0, \omega)$ and v_h and v_j are independent for $h \neq j$.

In addition to the prior distributions (3), we consider the following prior information with the hierarchical structure,

$$\begin{aligned} \log y_h^* &\sim N(\mu, \tau), \quad \omega \sim IG(c_*, d_*), \quad \mu \sim N(\mu_*, \sigma_*^2), \\ \tau &\sim IG(a_*, b_*), \end{aligned} \quad (8)$$

where $IG(a, b)$ denotes an inverted gamma distribution with a shape parameter a and a scale parameter b .

8.2.2.1 The FCDs of γ , Σ^{-1} , μ and τ

We write the parameter set as $\theta = \{\gamma, \Sigma^{-1}, (y_h^{*- \lambda}), \omega, \tau\}$. Given the prior information (3) and (8) and the model (7), we can easily derive the following FCDs of parameters. The FCD of γ is

$$\gamma | \dots \sim N(\gamma_{**}, \Phi_{**}), \quad (9)$$

where

$$\begin{aligned}\Phi_{**} &= (\Sigma^{-1} \otimes Y_*' Y_* + \Phi_*^{-1})^{-1}, \\ \gamma_{**} &= \Phi_{**} [\Phi_*^{-1} \gamma_* + (\Sigma^{-1} \otimes I_2) \text{vec}(Y_*' W)], \\ Y_* &= \begin{bmatrix} 1 & y_1^{*-2} \\ \vdots & \vdots \\ 1 & y_H^{*-2} \end{bmatrix}.\end{aligned}$$

The FCD of Σ^{-1} is

$$\Sigma^{-1} | \dots \sim W(G_{**}^{-1}, \nu_{**}), \quad (10)$$

where

$$G_{**} = (W - Y_* B)'(W - Y_* B) + G_*, \quad \nu_{**} = \nu_* + H.$$

The FCD of ω is

$$\omega | \dots \sim IG(c_{**}, d_{**}), \quad (11)$$

where

$$\begin{aligned}d_{**} &= \frac{1}{2} \sum_{h=1}^H (x_h^* - x_h^{*-})^2 + d_*, \quad c_{**} = c_* + \frac{H}{2}, \\ x_h^* &= \log y_h, \quad x_h^{*-} = \log y_h^*.\end{aligned}$$

The FCD of μ is

$$\mu | \dots \sim N(\mu_{**}, \sigma_{**}^2), \quad (12)$$

where

$$\sigma_{**}^2 = \left(\frac{H}{\tau} + \frac{1}{\sigma_*^2} \right)^{-1}, \quad \mu_{**} = \sigma_{**}^2 \left(\frac{1}{\tau} \sum_{h=1}^H x_h^* + \frac{\mu_*}{\sigma_*^2} \right).$$

The FCD of τ is

$$\tau | \dots \sim IG(a_{**}, b_{**}), \quad (13)$$

where

$$b_{**} = \frac{1}{2} \sum_{h=1}^H (x_h^* - \mu)^2 + b_*, \quad a_{**} = a_* + \frac{H}{2}.$$

Using the FCDs of parameters, we can analyze the posterior distribution from the Gibbs sampler.

8.2.2.2 The Posterior Distribution of γ_h^*

The posterior distribution of γ_h^* is complex. Therefore, we employ a random walk sampler for $x_h^* = \log y_h^*$.¹ Let $p(x_h^*)$ denote a posterior density of a parameter x_h^* . The candidate x is drawn according to the process $x = x_h^* + z$. We assume that the density of z is symmetric, that is $q(z) = q(-z)$. The random walk sampler can be described as follows:

1. At the $j+1$ th iteration, draw a $z^{(j+1)}$ from $q(z)$ and put $x^{(j+1)} = x_h^{*(j)} + z^{(j+1)}$.

2. Calculate the probability of move

$$p = \min \left\{ \frac{p(x^{(j+1)})}{p(x_h^{*(j)})}, 1 \right\}.$$

3. Generate u from a uniform distribution on $(0, 1)$.
4. If $u \leq p$, $x_h^{*(j+1)} = x^{(j+1)}$, otherwise, $x_h^{*(j+1)} = x_h^{*(j)}$.

¹ See, for example, Chib and Greenberg (1995).

8.2.3 Bayes Factor

The model selection in the Bayesian approach is implemented by the Bayes factor (see Gelfand (1996)). If Z denotes the actual observations and $f(Z | M_i)$ denotes the marginal density under the model M_i , the Bayes factor for the models M_i and M_j is defined as:

$$BF_{ij} = \frac{f(Z | M_i)}{f(Z | M_j)} \quad (14)$$

There are several importance-sampling and its related estimators of the marginal density based on a sample from the posterior distribution. In section 3, we use the importance-sampling estimator,

$$\hat{f}(Z | M_i) = \frac{1}{\|1/L_{post}\|} \quad (15)$$

where L_{post} denotes the likelihood evaluated by the posterior distribution (see Raftery (1996, p. 69)).

8.3 Empirical HOGLEX Engel Results and Implications for Social Security and Welfare Policies in Thailand and the Philippines

In this section, we report the estimates of the HOGLEX Engel model for a total of 20 important socio-demographic cohorts classified for Thailand and the Philippines. The estimates are derived from the HES unit records or microdata of the two countries and the Bayesian framework discussed in the previous section. Since only three major subsets (defined in terms of the value of λ) of the HOGLEX Engel model were considered here, the selection among these subsets is based on our dataset and, as usual, also on the Bayes factor to produce the preferred HOGLEX Engel model for each of our cohorts. Each preferred HOGLEX Engel model is therefore associated with an appropriate empirical value of λ that is consistent with the information from the sample data.

For each HES cohort dataset, our model also consists of five broadly defined commodities: (1) food, (2) clothing, (3) housing, (4) medical care, and (5) miscellaneous goods and services, and it is estimated for 20 (4×5) socio-demographic cohorts defined by household composition (i.e., by the number of adults and children in each household). These types are here denoted by (NoA, NoC) where NoA refers to the number of adults and NoC denotes the number of

The data used are household unit records from the 1988 Socio Economic Survey (SES) in Thailand and the 1988 Family Income and Expenditure Survey (FIES) of the Philippines. For the Thailand's SES, the sample of households is designed to represent all private, non-institutional households in Thailand that can be found in municipalities, sanitary districts or villages. The 1988 SES utilized a stratified three-stage sampling design to collect some 11500 sample households. The primary and secondary sampling units were the *amphoe* and the block or village, respectively. Households were the ultimate sampling units. For the Philippines' FIES, the survey involved the interview of a national sample of about 18500 households deemed sufficient to provide reliable estimates of income and expenditure levels for each province of the country, including key cities. The 1988 FIES, conducted between February 1988 and January 1989, used a two-stage cluster sampling design where the urban and rural areas of each province were the principal domains of the survey. The primary sampling units are the *barangays* and the households within each *barangay* comprise the secondary sampling units.

The operational definition of the household appears comparable for both surveys, that is, a household refers to a group of persons with common meal and other living arrangements. In both countries, it is common to find 'extended family' type households composed of the nuclear family plus one or more other relatives and/or domestic helpers. The households in these economies thus tend to be larger in size relative to those in more advanced countries.

In the study, a great deal of effort was made to ensure that the various expenditure categories have comparable compositions of detailed items. In all cases, expenditure refers to that of the household's rather than for selected individuals in the population. There is a slight difference in the demographic grouping of children between the two surveys. For Thailand, children refer to all those aged 15 years or younger; while for the Philippines, a child is defined as anyone who is aged up to 14 years old. This slight discrepancy is ignored and assumed not to significantly affect the results.

In our estimation of the HOGLEX Engel models below, we have rather pragmatically chosen the following values for the hyperparameters,

$$\begin{aligned} \gamma_* &= 0, \quad \Phi_* = 1000 \times I_{2m}, \quad G_* = 0.001 \times I_m, \quad \nu_* = 5, \\ \mu_* &= 0, \quad \sigma_*^2 = 1000, \quad c_* = 5, \quad d_* = 0.01, \quad a_* = 5, \quad b_* = 0.01, \end{aligned}$$

and use a normal density as a candidate transition kernel of random walk sampler, $q(z)$. We run the MCMC algorithm for 10,000 iterations following a burn-in phase of 2,000 iterations. All results reported in this section are performed by Ox version 3.2 (see Doornik, 2001).

First we note that since the dispersion parameters in the prior distributions are large, the Bayesian parameter estimates in both HOGLEX Engel models without and with measurement errors are almost the same as the MLE estimates.² One

² These estimates can be obtained from the authors.

interesting approach in this case would be to choose a set of alternative informative priors (based on previous studies in the countries in-focus or other studies for similar countries) for our models and to re-estimate the models and to compare the results. As one of our objectives in the present chapter is a comparison of three subsets of the HOGLEX Engel model, we adopt neither this approach nor report those estimated Bayesian parameter values of the models in each socio-demographic cohort.

The Bayesian estimation of our HOGLEX Engel four-commodity models and the selection of the preferred empirical model for each of the 20 cohorts for the Philippines and Thailand are given in Tables 8.1 and 8.2.

Table 8.1 reports the ranking, according to the Bayes factor, of three subsets of the HOGLEX Engel model without measurement errors. For the Philippines, and in all 20 socio-demographic cohorts under study, the value of $\lambda = 0$ (for an AIDS system) is obtained. For Thailand, the value of $\lambda = 0$ is selected in most cohorts, except in three cohorts ((NoA, NoC) = (1, 1), (3, 4) and (4, 3)), where $\lambda = -1$ (a RECIPROCAL system) is selected.

Table 8.2 shows the ranking, also according to the Bayes factor, of three subsets of the HOGLEX Engel models with measurement errors. For the Philippines, the value of $\lambda = 0$ is obtained. For Thailand, in four cohorts ((NoA, NoC) = (1, 2), (1, 3), (1, 4) and (2, 4)), the selected values of λ are different from Table 8.1.

What are then the implications of our findings for social security and welfare policy analysis in Thailand and the Philippines?

As has been mentioned earlier, the estimable value of λ represents the effects of the shape of income (total expenditure) distribution on budget shares. Suppose that an analyst assumes a priori that this value is say 1 (that is, the model used is LINEX) when it should be 0 (that is the model used should be AIDS) for a given dataset or cohort in Thailand, the consequence of such a mistake can be substantial in the calculation of mean incomes. More importantly, it can be costly (beneficial) for the social security or welfare recipients if a social security or welfare policy is based on mean incomes that are underestimated (overestimated) in this case. Our empirical findings reported in Tables 8.1 and 8.2 indicate that the conventional adoption of a specific demand system (that is, either LINEX, AIDS or RECIPROCAL) for all cohorts in our dataset is inappropriate.

The problem does not rest there. Suppose in addition that if we neglect the presence of measurement errors in total expenditure in the HOGLEX Engel model in particular or in the HOGLEX demand system in general when these errors exist, the results can also lead us to making mistakes in practical analysis of social security or welfare economics. The mistakes are in the measurement of mean income which is dependent on the value λ . Using Equation (2.13) in Deaton and Muellbauer (1980, p. 156) or a similar formula in Tran Van Hoa (1985), we can write the representative total expenditure (income) as follows:

$$y_0 = \left[\frac{\sum_h y_h^{1-\lambda}}{\sum_h y_h} \right]^{-1/\lambda} \quad (16)$$

If $\lambda = 0$, we can define y_0 in a similar manner to Deaton and Muellbauer (1980) as

$$y_0 = \exp \left[\frac{\sum_h y_h \log y_h}{\sum_h y_h} \right] \quad (17)$$

Tables 8.3 and 8.4 report the alternative measurements of mean income based on the observed and the unobserved household total expenditure in the results of the estimated HOGLEX Engle four-commodity model for all 20 cohorts in both Thailand and the Philippines. For both Thailand and the Philippines, the mean income from the RECIPROCAL model always exceeds that of the AIDS and LINEX in that descending order. When $\lambda = 1$, y_0 becomes the arithmetical mean $\bar{y}$. However, from Tables 8.1 and 8.2, the HOGLEX Engel model with $\lambda = 1$ is not selected by the Bayes factor with the exception of one cohort ((NoA, NoC) = (1, 2), (1, 4) and (3, 1) for Thailand in the model with measurement errors). Therefore, $\bar{y}$ is inappropriate as the measurement of mean household total expenditure. Except the above case, $\bar{y}$ underestimates y_0 . From our findings and their potential implications for social security and welfare policy formulation and implementation however, it is important to note the discrepancy of mean household incomes calculated with the parameter estimates from three different subsets of the HOGLEX Engel models (LINEX, AIDS and RECIPROCAL).

In the Bayesian estimation of the HOGLEX demand model with measurement errors, we can easily get the three alternative measurements of mean household income based on the unobserved household total expenditure y^* . This is an important merit of using Bayesian analysis. Since the posterior mean of ω is small for all cases, the values of the three alternative measurements of mean household income based on y^* are similar to those based on the observed household total expenditure y .

In the present study, the evidence appears however to support the use of the AIDS or RECIPROCAL model for most cohorts and its mean income as more reliable and accurate information for use in policy analysis in welfare economics.

8.4 Concluding Remarks

In this chapter, we have focused on an economically integrable and statistically flexible demand system in which many well-known demand systems are simply subsets. The flexibility means that there is no need for investigators in this area of work to be burdened (or obsessed) for various subjective or non-subjective reasons with a specific functional form, determined a priori or subjectively and without relevance to the data on hand. The exact functional form within a wide class of functions can be determined empirically from the existing dataset by simply using the HOGLEX demand system either in a classical or Bayesian context.

Using unit record data, we have fitted the HOGLEX Engel model for a total of 20 cohorts of population for two major developing economies in the ASEAN, namely Thailand and the Philippines, to find out the income (total expenditure) effects on consumption and, more importantly, the level of mean income appropriate for each of these 20 cohorts in each country. Since mean income has been the basis for the calculation of social security and welfare benefits, tax exemptions, pensions, family subsidies, school allowance, compensation, and so on, an accurate measurement of mean income is in our opinion crucially important for a good, effective, and fair social security and welfare system in any country. In our findings, we have obtained what we regard as optimal and data-consistent models for demand studies even at the very disaggregated level of the population and also for social security and welfare policy analysis in Thailand and the Philippines.

We have also estimated three important and well-known subsets of the HOGLEX Engel model under the condition of no measurement errors, calculated their representative household total expenditures and selected, using the Bayes factor, the best models among them for policy studies. We have also considered these models with the introduction of measurement errors in total expenditure. Using the simulation-based Bayesian analysis (MCMC), we have estimated the models with measurement errors without resorting to using extraneous information in the form of additional instrumental variables satisfying the Mann-Wald conditions. This is one of the important merits of Bayesian analysis when compared to the classical or conventional estimation of our models.

From our empirical analysis using HES data for Thailand and the Philippines, $\lambda = 1$ (the linear expenditure system) has not been found, by the Bayes factor, appropriate for most socio-demographic cohorts in both countries. Therefore, $\bar{y}$ is inappropriate as the measurement of mean household total expenditure and, as a result, as a basis for formulating social security and welfare policies. The costs of using $\bar{y}$ in this case are high to the social security and welfare recipients. We have also found that in a number of cohorts for these countries, the results can lead us to mistakes in practical social security policy analysis and welfare economics, if we neglect the incidence of measurement errors in total expenditure.

We have only considered, for illustration, three important subsets of the Engel version of the HOGLEX demand system in this paper. But the importance of including other appropriate subsets for further analysis of the HOGLEX system

and the available dataset should not be overlooked when adequate recourses are available. We have also considered measurement errors in total expenditure (income) in this paper. However, as Lewbel (1996) discussed, if total expenditure is observed with measurement errors, its components (that is, expenditures and budget shares for each commodity) also have measurement errors. This type of demand models with measurement errors on both the left and right hand sides can be easily estimated by the Bayesian approach (see Hasegawa and Kozumi, 2001). This issue for the socio-demographic cohorts under study in Thailand and the Philippines will be considered in future.

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Table 8.1 Model Ranking (Without Measurement Errors)

No. of Adults λ	Thailand No. of Children				Philippines No. of Children					
	0	1	2	3	4	0	1	2	3	4
$\lambda=0$	1	2	1	1	1	1	1	1	1	1
1 $\lambda=1$	3	3	2	3	2	2	3	3	3	3
$\lambda=-1$	2	1	3	2	3	3	2	2	2	2
NoO ^a	927	248	152	82	17	321	295	396	415	277
$\lambda=0$	1	1	1	1	1	1	1	1	1	1
2 $\lambda=1$	2	2	2	3	3	2	2	2	2	3
$\lambda=-1$	3	3	3	2	2	3	3	3	3	2
NoO	1289	1440	1350	694	176	641	947	1591	1720	1490
$\lambda=0$	1	1	1	1	2	1	1	1	1	1
3 $\lambda=1$	2	3	2	2	3	3	2	3	2	2
$\lambda=-1$	3	2	3	3	1	2	3	2	3	3
NoO	751	579	535	227	79	242	299	344	339	302
$\lambda=0$	1	1	1	2	1	1	1	1	1	1
4 $\lambda=1$	2	2	3	3	2	2	3	3	3	2
$\lambda=-1$	3	3	2	1	3	3	2	2	2	3
NoO	451	433	301	145	46	87	125	153	127	114

^a NoO=Number of observations.

Table 8.2 Model Ranking (With Measurement Errors)

Thailand		Philippines			
No. of Adults	No. of Children	No. of Children			
λ	0 1 2 3 4	0	1	2	3 4
$\lambda=0$	1 3 2 3 3	1	1	1	1 1
1 $\lambda=1$	3 2 1 2 1	3	3	3	3 2
$\lambda=-1$	2 1 3 1 2	2	2	2	2 3
NoO ^a	927 248 152 82 17	321	295	396	415 277
$\lambda=0$	1 1 1 1 3	1	1	1	1 1
2 $\lambda=1$	2 2 2 3 2	2	2	2	2 3
$\lambda=-1$	3 3 3 2 1	3	3	3	3 2
NoO	1289 1440 1350 694 176	641	947	1591	1720 1490
$\lambda=0$	1 2 1 1 2	1	1	1	1 1
3 $\lambda=1$	2 1 2 2 3	3	2	3	2 2
$\lambda=-1$	3 3 3 3 1	2	3	2	3 3
NoO	751 579 535 227 79	242	299	344	339 302
$\lambda=0$	1 1 1 2 1	1	1	1	1 1
4 $\lambda=1$	2 3 2 3 3	3	3	3	3 2
$\lambda=-1$	3 2 3 1 2	2	2	2	2 3
NoO	451 433 301 145 46	87	125	153	127 114

^a NoO=Number of observations.

Table 8.3 Alternative Measurements of Observed Mean Household Total Expenditures

No. of Adults	Thailand			
	No. of Children			
λ	0	1	2	3
$\lambda=0$	4625.17*	3967.76	5079.60*	4306.61*
$\lambda=1$	3450.02	3134.12	3771.34	3422.80
$\lambda=-1$	6678.46	5184.06*	6982.01	5372.68
$\lambda=0$	6251.48*	6852.82*	6262.59*	6766.36*
$\lambda=1$	4607.67	4636.40	4609.11	5043.85
$\lambda=-1$	8794.33	14798.77	9639.18	9556.61
$\lambda=0$	7522.37*	7470.17*	7792.20*	7291.13*
$\lambda=1$	5342.45	5273.36	5600.06	5455.39
$\lambda=-1$	11195.19	12211.22	12387.50	10925.94
$\lambda=0$	9562.92*	10494.22*	9584.40*	8156.09
$\lambda=1$	6910.18	6816.58	6372.45	5994.54
$\lambda=-1$	13411.08	18973.53	15541.43	11202.18*
Philippines				
No. of Adults	No. of Children			
	No. of Children			
λ	0	1	2	3
$\lambda=0$	89579.24*	30181.48*	36341.19*	39201.78*
$\lambda=1$	24469.15	22339.82	27252.26	29583.28
$\lambda=-1$	268864.93	40466.95	50729.11	52472.70
$\lambda=0$	44729.31*	53692.04*	47073.02*	45478.56*
$\lambda=1$	23567.01	31158.97	33146.61	33640.53
$\lambda=-1$	137559.47	132026.12	78598.58	68389.91
$\lambda=0$	96450.41*	74884.89*	72173.63*	60205.00*
$\lambda=1$	43698.52	43715.81	49338.42	45716.30
$\lambda=-1$	222631.59	157216.39	123948.56	84842.66
$\lambda=0$	82921.80*	81752.43*	101077.50*	105076.28*
$\lambda=1$	48007.67	58410.46	63537.14	65387.94
$\lambda=-1$	161008.67	117539.53	177483.96	184360.51

* denotes the selected model without measurement errors.

Table 8.4 Alternative Measurements of Unobserved Mean Household Total Expenditures

No. of Adults	Thailand			
	No. of Children			
λ	0	1	2	3
$\lambda=0$	4625.174*	3967.671	5079.594	4306.674
$\lambda=1$	3450.024	3134.082	3771.308*	3423.007
$\lambda=-1$	6678.458	5184.008*	6981.942	5372.802*
$\lambda=0$	6251.479*	6852.816*	6262.595*	6766.369
$\lambda=1$	4607.672	4636.398	4609.108	5043.837
$\lambda=-1$	8794.333	11798.754	9639.174	9556.598
$\lambda=0$	7522.374*	7470.181	7792.189*	7291.092*
$\lambda=1$	5342.409	5273.337*	5600.039	5455.365
$\lambda=-1$	11195.191	12211.232	12387.472	10925.943
$\lambda=0$	9562.924*	10494.218*	9584.436*	8156.055
$\lambda=1$	6910.174	6816.581	6372.427	5994.508
$\lambda=-1$	13411.094	18973.498	15541.386	11202.188*
Philippines				
No. of Adults	No. of Children			
	No. of Children			
λ	0	1	2	3
$\lambda=0$	89579.223*	30181.469*	36341.181*	39201.776*
$\lambda=1$	24469.168	22339.798	27252.240	29583.273
$\lambda=-1$	268865.06	40466.949	50729.090	52472.721
$\lambda=0$	44729.279*	53692.048*	47073.014*	45478.563*
$\lambda=1$	23567.011	31158.970	33146.612	33640.536
$\lambda=-1$	137559.520	132026.133	78598.573	68389.908
$\lambda=0$	96450.378*	74884.884*	72173.619*	60204.993*
$\lambda=1$	43698.519	43715.827	49338.398	45716.305
$\lambda=-1$	222631.584	157216.450	123948.545	84842.649
$\lambda=0$	82921.900*	81752.481*	101077.474*	105076.219*
$\lambda=1$	48007.649	58410.475	63537.101	65387.918
$\lambda=-1$	161008.746	117539.526	177483.905	184360.412

* denotes the selected model with measurement errors.