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Departamento de Economía
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (341) 624-9875

ESTIMATING DEMAND FOR FOOD COMMODITIES BY INCOME GROUPS IN INDONESIA

Helen Jensen and Justo Manrique*

Abstract

An analysis of the structure of demand was performed on household data, classified into income groups for urban Indonesia. A demographically augmented Linearized Almost Ideal Demand System was used to estimate the structural parameters of the demand equations. Endogenous switching regressions techniques yielded unbiased and consistent demand parameter estimates for the low income group, which had a large number of zeros for some food groups. Standard seemingly unrelated equation techniques were used to estimate the demand parameters for the other income groups. The results showed demands for the medium-high and high income households to be responsive to prices, income and demographic variables. Demands for the medium-low income households were responsive to income and prices only. Demands for low-income households were responsive to income and prices of rice and fish only.

Key Words
Endogenous Switching Regressions, Income Groups, Zeros, Indonesia.

*Helen Jensen, Associate Professor, Department of Economics, Iowa State University, Ames, Iowa, USA; Justo Manrique, Visiting Professor, Departamento de Economía, Universidad Carlos III de Madrid. Correspondence to: Departamento de Economía, Universidad Carlos III de Madrid, Calle Madrid, 126, 28903 Getafe (Madrid), Spain.

Estimating Demand for Food Commodities by Income Groups in Indonesia

1. Introduction and Background

The process of liberalizing the agricultural sector is under way in many countries. Budget problems, macroeconomic unbalances, the high costs of the agricultural support programs as well as prospects for the General Agreement on Tariffs and Trade (GATT) are the main reasons for this change in policy. These reforms are likely to lead to food price adjustments.

Such price changes, however, can have differential effects on consumers' well-being. The fact that consumption patterns vary by income level means that welfare effects also vary for different income groups when commodity prices change (Pinstrup-Andersen and Caicedo, 1978). Under these conditions, aggregate demand analysis is not very useful and may be misleading if policy makers are concerned with the effects of these adjustments on the well-being of specific target groups. Specific demand parameters by income group not only measure the welfare effects caused by given price policies accurately but also allow the design of compensation schemes for the poor based on specific commodities (Pinstrup-Andersen et al. 1976; Pinstrup-Andersen and Caicedo, 1978; Kennes, 1983).

In addition to the fact that people from different income groups have different consumer behavior, there are other reasons to estimate demand systems for different income groups instead of in aggregate.

First, it is difficult to incorporate the effects of income distribution into an aggregate demand analysis. Researchers often use average expenditure as a representative level of income and assume that the approximation error is small. This error, however, is minimized only if the expenditure distribution and the demographic composition remain relatively constant (Deaton and Muellbauer, 1980b). These assumptions generally do not hold.

In addition, income group specific demand parameters capture income class specific substitution effects that should not be ignored in policy formulation. Because consumption patterns for low-income consumers are generally less varied and hence contain fewer food items consumed than for others, approaches to estimating demand parameters that do not account for these zeros will lead to biased and inconsistent estimated demand parameters and elasticities. Conclusions based on such estimates would be erroneous and misleading.

A few studies have estimated demand elasticities by income group, for example, Teklu and Johnson (1988), Jarque (1987) and Kennes (1983). Most of these studies, however, do not follow a formal treatment of the household classification problem and instead take a pre-established (often government defined) income groupings or classify households on an ad-hoc basis. One exception is Jarque (1987), who presented a clustering procedure to treat the classification problem more formally. Although this procedure has good theoretical basis, its practical use and its importance for policymaking are limited. It requires very precise and specific information and can produce too many socioeconomic groups (raising the question of the relevance of many of them) and groups defined in terms of several qualitative variables. Finally Jarque's procedure requires a large number of observations.

The analysis presented in this paper is based on classification of households into income groups with different consumption behavior. Households showing similar consumption behavior are classified in the same group. The procedure proposed here is easy to implement, does not need a great deal of specific information, has good statistical foundation and sets specific income boundaries for the groups.

This paper has two basic objectives: (1) to develop a procedure to classify households into income groups and (2) to analyze expenditure patterns and the structure of demand for different income groups using data for Indonesia. The plan of this paper is as follows. Section 2 discusses data issues and the methodology to classify households into income groups and includes a brief analysis of patterns of consumption of these newly formed income groups. Section 3 presents the almost ideal demand system (AIDS) model, which incorporates demographic variables. In Section 4, the econometric methodology and the problems found in the empirical estimation of demand systems for different income groups are addressed. Empirical findings are discussed in section 5. Finally, Section 6 summarizes and concludes the study.

2. The Data and Classification of Households in Income Groups

2.1. Data issues

Data from the National Social and Economic Surveys (SUSENAS) of households in Indonesia were used in this study. The government of Indonesia periodically conducts these surveys to collect data related to expenditure and socioeconomic characteristics of Indonesian households. The surveys from 1981 (subround 1), 1984 and 1987 provide the basis of this study.

SUSENAS used a proportional random sample of households within a primary sampling unit (PSU); PSUs are subunits of census area segments. The selection of PSUs for these surveys was based upon a stratified sample design established for the Indonesian Census. The unit of observation for this study was a "representative" PSU household hereafter referred to as the household, which was constructed by dividing the aggregate levels of selected variables (demographic and expenditures) by the number of households in that PSU[1]. For this study, only observations belonging to the urban regions both on and off Java were used. In total, there were 3705 "representative household" observations for urban areas on and off Java for the three time periods.

Eight commodity groups formed the basis of the analysis: rice, meats, dairy, fish, palawija products (e.g., soybeans, corn, and cassava) wheat, fruits, and other foods and nonfoods. These commodity groups had similar nutritional components or source, were important to food policy concerns, were used in past studies of the Indonesian food sector, and met the need for a parsimonious model. In this study, we used unit values (expenditures divided by quantities) as "prices" because actual prices paid were not reported in the surveys.[2] Commodity group prices were obtained from the sum of prices of component food items which were weighted by respective budget shares.

Missing or unreported prices, required for estimating the demand system, were estimated by regressing observed prices on regional dummies and household total expenditures (cf. Heien and Pompelli, 1989). The estimated prices replaced the missing prices in the estimation of the demand system. Dagenais (1973) and Gourieroux and Monfort (1981) discuss the properties of the parameter estimates found by using data obtained in this way.

For nonfoods, quantities were not defined. Therefore, price indexes for housing, clothing, and other nonfood consumption were used as computed by the Central Bureau of Statistics for the province's most important regional cities. The aggregate price for the nonfood commodity group was computed using an average of the price indexes for housing, clothing and other nonfood consumption.

Total expenditures, the sum of expenditures on all commodities, were used as a measure of income for classifying households into income groups and for estimating the demand system.

2.2 Classification of households into income groups

The households were classified into income groups by establishing boundaries for groups in terms of differences in household behavior related to consumption patterns. Heteroskedasticity problems are common when cross sectional data are used in the estimation of parameters of Engel relations: food expenditures are almost completely explained by income for low-income households; for high-income households, food expenditures depend, to a greater extent, on other factors. In other words, when estimating food expenditures as explained by income, the values of the disturbances are likely to be small for low-income households and large for high-income households.

We exploited this fact in classifying households into income groups through an analysis of homogeneity of variances of residuals from Engel regressions. The procedure for classification included two basic steps: (1) estimation of Engel relations and (2) tests for homoskedasticity of variances.

First, an Engel function that included region, household demographics, and total expenditures was estimated for each of the i commodities. This equation was of the form

$$E_i = \alpha_{i0}\ \text{REGION} + \alpha_{i1}\ \text{AS1} + \alpha_{i2}\ \text{AS2} + \alpha_{i3}\ \text{AS3} + \alpha_{i4}\ \text{AS4} + \alpha_{i5}\ \text{AS5} + \alpha_{i6}\ \text{AS6} + \alpha_{i7}\ \text{TOTEXP} + \mu_i, \qquad (1)$$

where $\mu_i \sim \text{iid}\ (0, \nu_i^2)$.

E_i was expenditures in commodity group i (foods, nonfoods, fish, fruits, vegetables, and eggs); REGION was a dummy variable (Java=1, Off Java=0); AS1 was the average number of children 1-5 years per household; AS2 the average number of children 5-10 years; AS3 the average number of males 10-20 years; AS4 the average number of females 10-20 years; AS5 is the average number of males 20 years and more; and AS6 the average number of females 20 years and more; TOTEXP was the total expenditures per household. Data for the years 1981, 1984, 1987 were estimated independently.

Groups of observations having common variances (residuals) were plotted against total expenditures. Residuals were evaluated by visual inspection to classify observations into preliminary income groups for subsequent statistical testing. The testing for homoskedasticity of variances was by successive Goldfeld-Quandt tests.

Equation (1) was reestimated for each group of observations identified by visual inspection of residuals. Again, Goldfeld-Quandt tests were performed to see if the variances of the residuals of every adjacent pair of groups of observations were the same. Final boundaries were determined for every income group by repeating the classification of observations to a smaller number of groups around tentative boundary points. This process was repeated for each survey (1981, 1984, and 1987). Finally, the income groups were reconciled so that the same number of groups existed for every year. This approach allowed pooling the years of data into a consistent data series. By following this methodology, the (pooled) 3705 observations for urban areas reported in the 1981, 1984, and 1987 SUSENAS surveys were distributed into four income groups: low, medium-low, medium-high, and high.

2.3 Food participation rates

The percentage of households that reported expenditures on food groups within the PSU, defined as "participation rates," provides a good indication of expenditure patterns and is important for understanding the extent of the problem of zero expenditures for subsequent econometric analysis. Food group participation rates for urban Indonesia are presented in Table 1 for all three years.

Low-participation rates in meats, dairy products and some palawija products were present for low-income groups and high-participation rates in all commodity groups were observed for the high-income groups (Table 1). Rice was consumed by nearly all households regardless of income level.

3. The Basic Model

The linearized Almost Ideal Demand System (LA/AIDS) was used to estimate the structural parameters of the demand equations. Detailed derivations of the AIDS model are available in Deaton and Muellbauer (1980a,b). The general form of the derived share equation was

$$w_i = \alpha_i + \Sigma_j \gamma_{ij} \ln p_j + \beta_i \ln (X / P), \tag{2}$$

where w_i was the expenditure share of the i^{th} commodity, p_j is the price of the j^{th} commodity, X is total expenditures, and P is a price index such that

$$\ln P = \alpha_0 + \Sigma_i \alpha_i \ln p_i + ½ \Sigma_i \Sigma_j \gamma_{ij} \ln p_i \ln p_j \tag{3}$$

for the $i,j=1,\ldots,n$ commodities. The basic demand restrictions were expressed in terms of the model's coefficients

$$\Sigma_i \alpha_i = 1; \qquad \Sigma_i \gamma_{ij} = 0; \ \Sigma_i \beta_i = 0 \qquad \text{(adding up)}$$

$\Sigma_j \gamma_{ij} = 0$ (homogeneity)

$\gamma_{ij} = \gamma_{ji}$ for all i $(i \neq j)$. (symmetry) (4)

Differences in household behavior depend not only on prices and income but also on household characteristics and demographic factors. This relationship was maintained accomplished by adding parameters to the demand system; only these additional parameters depended on the demographic variables (Pollak and Wales, 1980, 1981). This demographic translating was used to incorporate demographic variables into the model so that

$$\alpha_i = \rho_{i0} + \Sigma_s \rho_{is} N_s, \tag{5}$$

where the N_s are the demographic variables (s = 1,..., d).

For estimation purposes, the price index P was approximated using Stone's index,

$$\ln P^* = \Sigma_i \bar{w}_i \ln p_i, \tag{6}$$

where $\bar{w}_i$ is the mean of the budget share.

The resulting system is

$$w_i = \rho_{i0} + \Sigma_s \rho_{is} N_s + \Sigma_j \gamma_{ij} \ln p_j + \beta_i \ln (X / P^*), \tag{7}$$

where i = 1,...,n and the adding-up restriction was now

$$\Sigma_i \rho_{i0} = 1; \Sigma_i \rho_{is} = 0; \Sigma_i \gamma_{ij} = 0; \Sigma_i \beta_i = 0 \tag{8}$$

where i=1,...,n and j=1,n and s=1,...d.

The uncompensated own, cross-price, and income elasticities for this system are

$$e_{ii} = [\gamma_{ii} - \beta_i w_i + \beta_i^2 \ln (\bar{X})] / w_i - 1, \tag{9}$$

$$e_{ij} = [\gamma_{ij} - \beta_i w_j + \beta_i \beta_j \ln (\bar{X})], \tag{10}$$

$$e_i = \beta_i / w_i + 1. \tag{11}$$

4. Estimation of Demand Systems per Income Group

The existence of a problem of zero expenditures for some of the commodities conditioned the methodology for the estimation of the demand systems. For the three higher income groups, standard estimation techniques were used because zero expenditures were not an important problem. For the low-income group, a limited dependent variable model was used.

4.1 The zero expenditure problem

As shown in Table 1, almost all households in the low income group had expenditures for rice, fruits, palawija crops, fish, other foods and non foods. The low-income households, often did not purchase dairy or meat commodities within the survey period. In addition, participation rates for the medium-low-, medium-high-, and high-income households were generally 90 percent for all commodity groups. These facts conditioned the econometric methodology for the estimation of the demand system.

From a statistical viewpoint, a large number of observations at the zero expenditure share boundary causes a nonzero mean for the disturbances and a probability of zero expenditures that is not negligible. Under these conditions, standard estimation methods yield biased and inconsistent estimates of the parameters because they do not take account of the nonzero mean of the disturbances (Amemiya, 1984; Wales and Woodland, 1983; Maddala, 1983). The problem of zero expenditures is quite frequent whenever disaggregated cross sectional data on commodity consumption are used in the estimation of demand systems (Wales and Woodland, 1983; Cox and Wohlgenant, 1988; Yen and Roe, 1989).

The traditional method used to deal with the limited dependent variable problem has been standard tobit analysis. The tobit method assumes that the decision to consume a given food item is determined by the same factors that determine the decision on the amount of food to be consumed (Lin and Schmidt, 1983; Lee and Brown, 1986). But, factors explaining the probability of consuming a food commodity may differ from those that explain the quantities. An alternative approach is a two-step decision process in which individuals first decide to consume some nonzero amount of a particular good and then, conditional on this decision, they choose the amount. This approach allows different sets of factors to explain expenditures on each outcome and different demand functions for the set of commodities when some of them are not consumed.

Switching regression models provide a method to model the consumption decision as a two-step decision process (Maddala, 1983). Lee and Brown (1986), for example, used a two-stage switching regression type model to examine food expenditures at home and away from home in the United States as individuals choose to belong to one group or another, i.e., by individual self-selection. This approach is followed in this paper.

4.2 Estimation of a demand system for the low income group

Relatively low participation rates for the dairy and meats commodity groups presented a problem of estimation for low-income households. Therefore, low-income households were divided into four groups or regimes:

those consuming (i) all commodities; (ii) all except meat; (iii) all except dairy; and (iv) all except meat and dairy.

Four alternative regimes were identified, based upon the outcomes of the discrete choices of consumption of meats and dairy products. Decisions regarding membership in one regime or another were the result of optimizing behavior. Endogenous switching among the four regimes can occur when individuals are not randomly assigned to each regime (Maddala, 1983; Maddala and Nelson, 1975; Huffman, 1988; Lee and Brown, 1986).

By letting w_7 and w_8 be the share equations for meats and dairy products, respectively, all N households were classified into four mutually exclusive subsamples (S_1, S_2, S_3, and S_4) based upon the discrete choices on w_7 and w_8:

S_1: households in which all w's have nonzero values,

S_2: households in which $w_8 = 0$, $w_i \neq 0$, and $i=1,\ldots,7$;

S_3: households in which $w_7 = 0$, $w_i \neq 0$, and $i=1,\ldots,6,8$;

S_4: households in which $w_7 = 0$, $w_8 = 0$, and $i=1,\ldots,6$.

All observations have a nonzero probability of being assigned to one of the four subsamples or regimes. This probability is determined by evaluating the following bivariate probabilities:

$$M_{11} = P(S_1) = P(w_1,\ldots,w_8 \neq 0)$$
$$= P\,[\; w_7^* = \delta_7'Z_7 + \eta_7 > 0 \quad,\; w_8^* = \delta_8'Z_8 + \eta_8 > 0 \;], \tag{12}$$

$$M_{10} = P(S_2) = P(w_1,\ldots,w_7 \neq 0,\; w_8 = 0)$$
$$= P\,[\; w_7^* = \delta_7'Z_7 + \eta_7 > 0 \quad,\; w_8^* = \delta_8'Z_8 + \eta_8 \leq 0 \;], \tag{13}$$

$$M_{01} = P(S_3) = P(w_1,\ldots,w_6 \neq 0,\; w_7 = 0,\; w_8 \neq 0)$$
$$= P\,[\; w_7^* = \delta_7'Z_7 + \eta_7 \leq 0 \quad,\; w_8^* = \delta_8'Z_8 + \eta_8 > 0 \;], \text{ and} \tag{14}$$

$$M_{00} = P(S_4) = P(w_1,\ldots,w_6 \neq 0,\ w_7 = w_8 = 0)$$
$$= P\,[\ w_7^* = \delta_7'Z_7 + \eta_7 \le 0\ \ ,\ w_8^* = \delta_8'Z_8 + \eta_8 \le 0\ \ ]. \tag{15}$$

In this context w_7^* and w_8^* are unobservable variables. But, one can observe two dummy variables $\tilde{w}_7$ and $\tilde{w}_8$ such that $\tilde{w}_7 = 1$ if $w_7^* > 0$, $\tilde{w}_7 = 0$ (otherwise), and $\tilde{w}_8 = 1$ if $\tilde{w}_8^* > 0$ or else $w_8 = 0$. Z_7 and Z_8 are vectors of explanatory variables, δ_7 and δ_8 are parameter vectors; and η_7 and η_8 are disturbance terms. Bivariate probit regressions can be used to obtain estimates of δ_7 and δ_8. These estimates, in turn, yield probabilities (12) through (15).

The disturbance terms of the conditional demands estimated without taking account of the probability of selection do not have a zero mean, and direct application of the standard estimation techniques will produce biased and inconsistent estimates. Adding a correction term for self-selectivity bias to each demand equation yields a new disturbance term, which has a zero mean. Probabilities (12) through (15) were used to construct estimates of selection terms for the demand equations and give the conditional demand systems corrected for selectivity bias.

For Regime 1 (S_1):

$$w_i = \rho_{i1} + \sum_{j=1}^{8} v_{ij1} \ln p_j + \beta_{i1} \ln (X/P^*) + \Sigma_s\, \rho_{is1} N_s$$

$$+ \tau_{1i1} A_{11} / M_{11} + \tau_{2i1} A_{21} / M_{11} + \epsilon_{i1} \qquad \text{if } i=1,\ldots,6;$$

or

$$+ A_{11} / M_{11} + \epsilon_{i1} \qquad \text{if } i=7;$$

or

$$+ A_{21} / M_{11} + \epsilon_{i1} \qquad \text{if } i=8; \tag{16}$$

For Regime 2 (S_2):

$$w_i = \rho_{i2} + \sum_{j=1}^{7} \gamma_{ij2} \ln p_j + \beta_{i2} \ln (X/P^*) + \Sigma_s \, \rho_{is2} \, N_s$$

$$+ \tau_{1i2} A_{12} / M_{10} + \tau_{2i2} \; A_{22} / M_{10} + \epsilon_{i2} \qquad \text{if} \quad i=1,\ldots,6;$$

or

$$+ A_{12} / M_{10} + \epsilon_{i2} \qquad \text{if} \quad i=7; \tag{17}$$

For Regime 3 (S_3):

$$w_i = \rho_{i3} + \sum_{j=1}^{6} \gamma_{ij3} \ln p_j + \gamma_{i83} \ln p_8 + \beta_{i3} \ln (X/P^*) + \Sigma_s \, \rho_{is3} \, N_s$$

$$+ \tau_{1i3} A_{13} / M_{01} + \tau_{2i3} A_{23} / M_{01} + \epsilon_{i3} \qquad \text{if} \quad i=1,\ldots,6;$$

or

$$+ A_{23} / M_{01} + \epsilon_{i3} \qquad \text{if} \quad i=8; \tag{18}$$

For Regime 4 (S_4):

$$w_i = \rho_{i4} + \sum_{j=1}^{6} \gamma_{ij4} \ln p_j + \beta_{i4} \ln (X/P^*) + \Sigma_s \, \rho_{is4} \, N_s$$

$$+ \tau_{1i4} A_{14} / M_{00} + \tau_{2i4} A_{24} / M_{00} + \epsilon_{i4} \qquad \text{if} \quad i=1,\ldots,6 \tag{19}$$

where τ_1 and τ_2 are parameter vectors conformable to A (the values for A are defined in Appendix A), and $E\epsilon_{ik} = 0$, $i = 1,\ldots,8$, $j = 1,\ldots,8$, and $k = 1,\ldots, 4$, and

Finally, the adding up, homogeneity and symmetry restrictions were imposed on the system of equations (16) through (19). The adding up restriction is now

$$\Sigma_i \, \rho_{ik} = 1; \qquad \Sigma_i \, \rho_{isk} = 0 \qquad (s=1,\ldots,d);\ (k=1,\ldots,4)$$

$$\Sigma_i \, \gamma_{ijk} = 0 \qquad \begin{array}{l} (k = 1,\ldots,4 \text{ regime}) \\ (j = 1,\ldots,8 \quad \text{if } k = 1) \\ (j = 1,\ldots,7 \quad \text{if } k = 2) \\ (j = 1,\ldots,6,8 \quad \text{if } k = 3) \\ (j = 1,\ldots,6 \quad \text{if } k = 4); \end{array}$$

$\Sigma_i \; \beta_{ik} = 0$ $\quad$ $(k = 1,\ldots,4)$;

$\Sigma_i \; \tau_{1ik} = 0$ $\quad$ $(i = 1,\ldots,6)$ $(k = 1,\ldots,4)$,

$\Sigma_i \; \tau_{2ik} = 0$ $\quad$ $(i = 1,\ldots,6)$ $(k = 1,\ldots,4)$.

4.3 Estimation of a demand system for the higher income groups

For the three higher income groups, the demand system represented by equation (7) subject to restrictions (4) and (8) was estimated by using Standard Iterative Seemingly Unrelated Regression Equation (ITSURE) techniques. This procedure produces maximum likelihood estimates for linear equation systems and produces parameter estimates invariant to the choice of the deleted equation. The omitted equation is the budget share of nonfood commodities.

The estimation of demand systems for the higher income groups used observations having positive expenditures only with the standard assumption of a multivariate normal disturbance distribution of the errors.

5. Empirical Results

To get the parameter estimates, a set of linearized AIDS models for the eight commodity groups was estimated. The variables included time and regional dummies, average number of people per age group, prices, and total expenditures. SAS was used to estimate the demand systems for the high-, medium-high-, and medium-low-income groups, and LIMDEP was used to estimate the demand systems for the low-income groups.

5.1 High-income group

Most estimated parameters of the AIDS were statistically significant (71 out of 112) for the highest income group. The statistical significance of these coefficients suggests that demands were responsive to prices, income, and demographic variables. A large number of the estimated cross-price coefficients, γ_{ij}, had t-values absolutely larger than 2 (28 out of 56). This correlation implies some degree of sensitivity of the budget shares to cross prices. All estimated own-price coefficients, γ_{ii}, were positive. Thus, ceteris paribus, a unit percentage increase in own prices yields a percentage increase in budget shares. Moreover, the price of nonfoods had a statistically significant effect on the share values of all the other commodity groups, whereas the prices of dairy, fruits, and palawija crops had little or no effect anywhere (except through P^* and the value share itself). All estimated β_i coefficients for the food groups were statistically significant and negative; the one for the nonfood group was positive. The signs indicated that, for the high-income group, all food groups were classified as necessities and the nonfood group was classified as a luxury.

Most demographic coefficients (36 out of 49) were statistically different from zero. The number of children, teenagers, and adults affected all commodity demands positively except nonfoods. Location on Java affected positively the demands for dairy, palawija crops, other foods, and nonfoods and negatively the demands for meats, rice, fruits, and fish. Time affected negatively the demands for meats and nonfoods and positively the other demands.

Table 2 presents the matrix of uncompensated price and total expenditure elasticities of demand. All the own-price elasticities were negative.

Strictly speaking, only nonfoods seemed price elastic. The estimated elasticity for palawija foods was very close to one. Rice, the staple food, was the least responsive to own price changes. All commodity groups were more responsive to other food and nonfood prices than to rice prices. Changes in the prices of fruits, milk, fish and palawija crops had little effect on any demand. In general, high income households were more responsive to own price changes than to cross price changes.

All food demands had total expenditure elasticities less than unity (necessities). Nonfoods were the only commodity group having a total expenditure elasticity of greater than one (luxury).

5.2 Medium-high-Income Group and Medium-low-Income Groups

Most estimated parameters of the AIDS for the medium-high and medium-low income groups were statistically significant. And, cross-price effects were statistically significant for about half of the commodity groups. For both income groups, all β_i coefficients were statistically significant and negative; thus, all the commodity groups were classified as necessities.

Most demographic coefficients were statistically different from zero. For the medium-high-income groups, almost all demands, except nonfoods, were affected positively by the number of children, teenagers, and adults. Fewer demographic variables were statistically significant for the medium-low-income group. For this group, additional family members affected the value shares of specific food groups, principally the ones that they consumed the most (rice and fish). Location on Java affected positively the demands for meats, palawija crops, other foods and nonfoods and negatively the demands for rice, fruits, dairy, and fish. Time affected negatively the demands for meats, fish, and nonfoods and positively all the other demands.

Tables 3 and 4 present the matrix of uncompensated price and income elasticities of demand for the medium-high- and medium-low-income groups, respectively. In general, households in these income groups showed greater own-price elasticities and stronger cross-price effects than households in the high-income group.

Although the own-price elasticities were negative and generally less than one, for the medium-high-income group, nonfoods, meats, and palawija crops were greater than, or nearly unity. Other foods and rice were the least responsive to own-price changes. Estimated price elasticities for the medium-low income group were generally greater (in absolute value) and showed stronger cross-price effects compared to high-income groups.

Most food demands had income elasticities smaller than unity (necessities). The nonfood group was the only commodity group having an expenditure elasticity of greater than one (a luxury good) for both income groups. Fish had a negative expenditure elasticity (an inferior good) for both groups; meat had a negative expenditure elasticity for the medium-low-income group. As observed in Table 1, as total expenditure increases fish consumption and (especially) dry fish consumption decrease.

5.3 Low-income group

A bivariate probit analysis was performed to construct estimates of the correction terms for self-selectivity bias and to better understand the meat and dairy product consumption decisions of the low-income households. The variables included in the bivariate probit estimated equations explaining meat and dairy consumption probabilities were numbers of children, teenagers, and adults; time dummies; and six regional dummies. The parameter estimates are reported in Table B-1, Annex B. The estimated correlation coefficient of the disturbances in the share of meat and share of dairy product equations turned out to be positive and statistically different from zero. The correlation implies that both equations were not statistically independent and that the disturbance terms were affected similarly by random shocks. Thus, the bivariate probit estimation of the participation equations is appropriate.

Time also affected positively the probability of consuming both meats and dairy products. The results also showed that the presence of teenagers in the household increased the probability of consuming meats only. The presence of the children and adults did not have a statistically significant effect on the probability of consuming either of the commodities. This result confirmed the tendency observed for the medium-low income group: additional family members increase only the demands of those food groups which they consume the most.

Based on equations 16 through 19, the conditional demand systems including demographic characteristics, prices, income, and the correction terms were estimated for each subsample (regime) of low-income households. In preliminary analysis, most demographic variables were not statistically significant and generated only small improvement in goodness of fit by including these variables (evaluated by using root mean square error and R^2's). To obtain a relatively parsimonious model, we estimated an alternative demand system, which included prices, income, and the correction terms only for the low-income households. The parameter estimates and corresponding price and income elasticities from these latter demand systems are discussed here.

Four conditional demand systems for the eight commodity groups with sample selection terms included were fit by SURE to each one of the four subgroups of low-income households. The included variables were logs of prices, log of real income, and the correction terms.

Tables B-2 through B-5 in annex B present the parameter estimates for the conditional AIDS models. Most of the γ_{ij} parameters were not significantly different from zero. This finding is consistent with the observed trend that shows a decreasing number of the cross price effects to be significantly different from zero as estimation proceeds from the highest to the lowest income group. It is also interesting to note that, in most instances, the prices of fish and rice had statistically significant effects on the value shares of some other commodity groups. Fish and rice are the food groups consumed mostly by low-income households.

Most β_i coefficients had t-values of greater than 2. The estimated parameters indicated foods to be necessities and nonfoods to be luxuries. For the subsample conditional on Smeat=0 and Smilk>0, fruits were also classified as luxuries. Most correction terms were significantly different from zero. This finding indicates the need to correct for the presence of self-selection bias.

Tables 5 through 8 present the matrices of uncompensated price and income elasticities of demand for the four subsamples of low-income households. In general, households in this income group showed greater own-price elasticities and stronger cross-price effects than households in the two highest income groups but smaller than those for the medium-low-income group.

For the four subsamples, all but one of the own price elasticities were negative. In general, demand was price inelastic. Nevertheless, two well-defined commodity groups showed price elastic demand: palawija crops and nonfoods. And, for three of the subsamples, rice was also own price elastic

(Smeat>0 and Smilk=0, Smeat=0 and Smilk>0, Smeat=0 and Smilk=0). Some commodity demands were responsive to other commodity prices. They were affected first by rice and nonfood prices and second by other foods. Changes in the prices of fruits, dairy products, and fish had little effect on most commodity demands.

Most food demands had income elasticities less than unity. Nonfoods was the only commodity group having an income elasticity of greater than one for all subsamples. The fruit group was income elastic for the subsample conditional on Smeat=0 and Smilk>0. Palawija crops had a negative income elasticity in the subsamples conditional on Smeat=0 (both for Smilk>0 and Smilk=0.)

6. Summary and Conclusions

Differences in consumption behavior and demand for food among income groups show the importance of estimating separate food demand parameters for income groups in Indonesia. In the first part of this paper, we presented a methodology to classify households in income groups based on the behavior of households regarding their acquisition of goods. The methodology is based on an analysis of homoskedasticity of variances of residuals from regressions of Engel relations. Indonesian data were used to regress total expenditures and household characteristics on total food expenditures, nonfood expenditures and food group expenditures. A tabular analysis of food participation rates showed that, for Indonesia, meats and dairy products were almost exclusively consumed by high-income households and that rice was consumed by nearly all households regardless of their income level. Meat and dairy product consumption patterns were used to differentiate consumption for the low-income households.

Demand system parameters were estimated for each of four income groups. Household characteristics, incorporated into the basic AIDS models by demographic translating techniques, explained differences in the households' preferences for all except the lowest income group. Endogenous switching regression techniques were used to obtain unbiased and consistent AIDS demand parameter estimates for the low-income group.

The results confirmed that the demand structure and the corresponding elasticities varied for different income groups. Demands for the high-income households were very responsive to prices, income, and demographic variables, whereas demands for the medium-low-income households were responsive mainly to income and prices. Demands of low-income households were most responsive to income and prices of rice and fish and not responsive to the deomographic variables.

In general, the estimated price and income elasticities for all income groups looked quite reasonable. The own price elasticities of demand become more price elastic (larger in absolute value) in moving from the high- to the low-income groups. For all income groups, there were two price-elastic food groups: nonfoods and palawija crops. Rice was also price elastic for most subsamples of low-income households. Cross-price elasticities were greater in absolute value for the low-income groups. Consistently, the price of nonfoods affected all demands. Rice prices also affected all demands but especially the demands of the low-income households. Nonfoods were a luxury for all income groups.

Such results have important consequences for food policy formulation and welfare analysis, particularly when income differences lead to markedly different food consumption patterns. Income group specific demand parameters can be used to make more accurate evaluation of the effects of alternative price policies on the well being of the different income groups, to design any specific target group compensation schemes based on specific food items (such as a food price subsidies, food cards, etc), and to design policies to the adequacy of diets for groups at risk of nutritional deficiencies. The price sensitivity of low-income households in Indonesia to rice prices both in own-commodity and cross-commodity demand suggests that increases in rice prices are likely to shift consumption of low-income households toward other secondary food crops more than for high-income groups. Although some other foods may be nutritionally superior to rice, welfare losses of such price increases may be relatively large for low-income households.

ENDNOTES

1. This aggregation was done in part to handle the large size of survey data, nearly 58,000 households for a single survey.

2. Deaton (1988) has reviewed the limitations of working with unit values instead of market prices. But, even if market prices would have been available, they also would have been subject to some of the measurement and recording errors attributed to unit values.

Table 1. Household participation rates for food expenditures by income group, urban Indonesia, all years

Food group	Income groups: Low	Medium Low	Medium High	High	Total
	Percent				
Meat (MEATS)	68.1	90.1	95.2	98.5	90.0
Dairy (MILK)	48.0	77.6	89.5	94.7	80.3
Rice (RICE)	99.5	99.9	100.0	100.0	99.9
Fruits (FRUITS)	94.5	98.6	99.3	99.7	98.4
Fish (FISH)	97.2	99.7	99.7	99.5	99.3
Fresh fish	87.2	96.7	98.5	98.8	96.2
Dry fish	89.8	92.5	93.0	89.6	91.7
Palawija (PALA)	98.4	99.2	99.7	99.7	99.4
Cassava	73.8	75.0	76.1	74.5	75.1
Corn	38.0	35.5	36.0	37.7	36.4
Nuts	66.6	79.5	86.1	91.7	82.1
Wheat	22.7	38.2	48.0	54.4	42.2

Note: Includes data from 1981, 1984, and 1987 SUSENAS.

Table 2. Uncompensated Price and income elasticities of demand for the high-income group

	MEATS	RICE	FRUITS	MILK	FISH	PALA	OFOOD	FOOD	INCOME
MEATS	-.89	-.19	.07	.12	.29	.08	.15	-.36	.69
RICE	-.10	-.42	.00	-.01	.06	-.02	.34	-.45	.26
FRUITS	.09	-.01	-.59	.03	.06	-.02	.29	-.46	.56
MILK	.19	-.04	.03	-.74	.06	.04	.15	-.42	.70
FISH	.38	.14	.06	.05	-.50	-.06	.53	-.98	.22
PALA	.11	-.04	-.02	.04	-.06	-.97	.31	-.05	.65
OFOOD	.03	.10	.04	.02	.07	.04	-.88	-.28	.74
NFOOD	-.01	-.03	-.01	-.01	-.02	-.01	-.05	-1.05	1.07

Table 3. Uncompensated Price and income elasticities of demand for the medium-high-income group

	MEATS	RICE	FRUITS	MILK	FISH	PALA	OFOOD	NFOOD	INCOME
MEATS	-.91	.27	.13	.07	.40	.12	.17	-.73	.25
RICE	.10	-.58	.05	.01	.18	.10	.21	-1.07	.10
FRUITS	.16	.17	-.77	.04	.19	-.02	.21	-.52	.43
MILK	.13	.02	.06	-.64	.11	.01	-.12	-.29	.71
FISH	.67	.88	.25	.10	-.66	.20	1.34	-2.78	-.82
PALA	.13	.31	-.02	.01	.13	-1.03	.56	-.64	.44
OFOOD	.02	.07	.02	-.01	.13	.08	-.51	-.71	.86
NFOOD	-.03	-.12	-.02	-.01	-.06	-.02	-.11	-1.11	1.14

Table 4. Uncompensated Price and income elasticities of demand for the medium-low-income group

	MEATS	RICE	FRUITS	MILK	FISH	PALA	OFOOD	NFOOD	INCOME
MEATS	-.81	1.41	.38	.18	.51	.17	.71	-2.56	-.85
RICE	.20	-.87	.07	.05	.17	.11	.13	-1.21	.15
FRUITS	.26	.33	-.83	.10	.23	-.05	.26	-.87	.45
MILK	.24	.45	.20	-.55	.36	.13	.10	-1.26	.23
FISH	.37	.88	.25	.20	-.63	.21	.66	-2.20	-.34
PALA	.07	.36	-.03	.05	.13	-1.02	.21	-.42	.54
OFOOD	.04	.01	.03	.00	.06	.03	-.83	-.30	.95
NFOOD	-.06	-.21	-.03	-.02	-.07	-.03	-.09	-1.26	1.19

Table 5. Conditional price and income elasticities of demand for the low-income group (Smeat>0 and Smilk>0)

	MEATS	RICE	FRUITS	MILK	FISH	PALA	OFOOD	NFOOD	INCOME
MEATS	-.53	-.54	-.08	.05	.45	.12	.29	-.28	.39
RICE	-.08	-.71	.03	-.01	.19	.08	-.21	-.64	.34
FRUITS	-.09	.21	-.75	.01	.30	-.27	.06	-.08	.54
MILK	.12	-.23	.03	-.29	.31	-.09	-.39	-.30	.84
FISH	.23	.62	.14	.07	-.84	-.03	.26	-1.11	.16
PALA	.08	.32	-.20	-.03	-.07	-1.09	-.23	.30	.91
OFOOD	.03	-.27	.00	-.02	.04	-.04	-.97	.25	.98
NFOOD	-.02	-.21	-.01	-.01	-.10	.00	.02	-1.38	1.19

Table 6. Conditional price and income elasticities of demand for the low-income group (Smeat>0 and Smilk=0)

	MEATS	RICE	FRUITS	FISH	PALA	OFOOD	NFOOD	INCOME
MEATS	-.91	.24	-.02	.35	.29	.16	-.78	.65
RICE	.03	-1.59	.03	.12	.16	.85	-1.86	.10
FRUITS	-.02	.27	-.73	.16	.01	.50	-.86	.64
FISH	.18	.46	.07	-.53	-.02	.28	-1.18	.70
PALA	.17	.78	.01	-.01	-1.45	.54	-.62	.42
OFOOD	.02	.85	.05	.07	.11	-.77	-1.35	.59
NFOOD	-.03	-.53	-.03	-.07	-.05	-.34	-1.53	1.31

Table 7. Conditional price and income elasticities of demand for the low-income group (Smeat=0 and Smilk>0)

	RICE	FRUITS	MILK	FISH	PALA	OFOOD	NFOOD	INCOME
RICE	-1.67	-.01	-.04	-.14	.28	.52	.15	.71
FRUITS	-.17	-1.14	-.13	-.32	-.40	-.55	1.36	1.32
MILK	-.71	-.26	.33	.11	.37	.16	-.41	.34
FISH	-.40	-.10	.01	-.63	.07	-.15	.22	.98
PALA	1.74	-.25	.13	.21	-2.06	.51	-.71	-.40
OFOOD	.53	-.06	.01	-.04	.07	-.79	-.68	.63
NFOOD	-.03	.03	-.01	.01	-.05	-.19	-1.28	1.16

Table 8. Conditional price and income elasticities of demand for the low-income group (Smeat=0 and Smilk=0)

	RICE	FRUITS	FISH	PALA	OFOOD	NFOOD	INCOME
RICE	-.98	-.02	.17	.32	.29	-1.38	.31
FRUITS	-.28	-.87	.19	-.50	1.25	-.72	.94
FISH	.50	.05	-.48	.08	.40	-1.29	.58
PALA	1.61	-.19	.15	-1.62	-.01	-.49	.09
OFOOD	.29	.12	.15	-.02	-.58	-.93	.61
NFOOD	-.42	-.02	-.12	-.05	-.25	-1.46	1.28

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APPENDIX A

$A_{11} = \sigma_7^2\ f_7\ (1-F_8) + \sigma_{78}\ f_8\ (1-F_7)$

$A_{21} = \sigma_8^2\ f_8\ (1-F_7) + \sigma_{78}\ f_7\ (1-F_8)$

$A_{12} = \sigma_7^2\ f_7\ (1-F_8^*) + \sigma_{78}\ f_8\ (1-F_7)$

$A_{22} = \sigma_8^2\ f_8\ (1-F_7) + \sigma_{78}\ (1-F_8^{**})$

$A_{13} = \sigma_7^2\ f_7\ (1-F_8^{**}) + \sigma_{78}\ f_8\ (1-F_7^*)$

$A_{23} = \sigma_8^2\ f_8\ (1-F_7^{**}) + \sigma_{78}\ f_7\ (1-F_8^*)$

$A_{14} = \sigma_7^2\ f_7\ F_8 - \sigma_{78}\ f_8\ F_7$

$A_{24} = \sigma_8^2\ f_8\ F_7 - \sigma_{78}\ f_7\ F_8$

where

$f_7 =$ Density of $\epsilon_7 \sim N(0,\sigma_7^2)$

evaluated at $f\ [\ -\alpha_7 - \sum_{j=1}^{7} \gamma_{7j} \ln P_j - \beta_7 \ln (X/P^*)\ ]$

$f_8 =$ Density of $\epsilon_8 \sim N(0,\sigma_8^2)$

evaluated at $f\ [\ -\alpha_8 - \sum_{j=1}^{7} \gamma_{8j} \ln P_j - \beta_8 \ln (X/P^*)\ ]$

$F_7 =$ Distribution function of $N(0,\sigma_7^{*2})$

where $\sigma_7^{*2} = \sigma_7^2 - (\sigma_{78}^2/\sigma_8^2)$, evaluated at

$$F\ [\ -\alpha_7 - \sum_{j=1}^{8} \gamma_{7j} \ln P_j - \beta_7 \ln (X/P^*)$$

$$- (\sigma_{78}/\sigma_8^2)\ \ (-\alpha_8 - \Sigma_j^{8}\ \gamma_{8j} \ln P_j - \beta_8 \ln (X/P^*))\ ]$$

$$F_7^* = F\left[\alpha_7 + \sum_{j=1}^{8} \gamma_{7j} \ln P_j + \beta_7 \ln(X/P^*) - (\sigma_{78}/\sigma_8^2)\left(-\alpha_8 - \Sigma_j^{8} \gamma_{8j} \ln P_j - \beta_8 \ln(X/P^*)\right)\right]$$

$$F_7^{**} = F\left[-\alpha_7 - \sum_{j=1}^{8} \gamma_{7j} \ln P_j - \beta_7 \ln(X/P^*) + (\sigma_{78}/\sigma_8^2)\left(-\alpha_8 - \Sigma_j^{8} \gamma_{8j} \ln P_j - \beta_8 \ln(X/P^*)\right)\right]$$

F_8 = Distribution function of $N(0, \sigma_8^{*2})$

where $\sigma_8^{*2} = \sigma_8^2 - (\sigma_{78}^2/\sigma_7^2)$, evaluated at

$$F\left[-\alpha_8 - \sum_{j=1}^{8} \gamma_{8j} \ln P_j - \beta_8 \ln(X/P^*) - (\sigma_{78}/\sigma_7^2)\left(-\alpha_7 - \Sigma_j^{8} \gamma_{7j} \ln P_j - \beta_7 \ln(X/P^*)\right)\right]$$

$$F_8^* = F\left[\alpha_8 + \sum_{j=1}^{8} \gamma_{8j} \ln P_j + \beta_8 \ln(X/P^*) - (\sigma_{78}/\sigma_7^2)\left(-\alpha_7 - \Sigma_j^{8} \gamma_{7j} \ln P_j - \beta_7 \ln(X/P^*)\right)\right]$$

$$F_8^{**} = F\left[-\alpha_8 - \sum_{j=1}^{8} \gamma_{8j} \ln P_j - \beta_8 \ln(X/P^*) + (\sigma_{78}/\sigma_7^2)\left(-\alpha_7 - \Sigma_j^{8} \gamma_{7j} \ln P_j - \beta_7 \ln(X/P^*)\right)\right]$$

Annex B

Table B-1 Bivariate probit explanation of participation in meats and dairy consumption

Variables	Consumption of meats	Consumption of dairy
Intercept	-.133 (-.3)[a]	-.184 (-.5)
Region3	.374 (2.2)	-.368 (-2.3)
Region5	.535 (2.7)	-.812 (-4.1)
Region6	.088 (.3)	-.105 (-.4)
Region7	-.302 (-1.3)	.978 (.4)
Region8	-.594 (-.6)	.100 (.1)
T84	.129 (.9)	.332 (2.3)
T87	.450 (3.0)	.428 (3.0)
Demo1	-.066 (-.6)	.078 (.7)
Demo2	.206 (2.0)	-.072 (-.7)
Demo3	.697 (.5)	.113 (.9)
Rho (correlation coefficient)		.434 (6.6)

[a] The numbers in parentheses are asymptotic t-ratios.

Table B-2 Conditional parameter estimates of the AIDS model for the low-income group, share of meats>0, and share of dairy products>0

	Meats	Rice	Fruits	Dairy	Fish	Palawija crops	Other Foods	Non Foods
Intercept	.0557	.4681	.0705	-.0050	.1575	.0315	.2028	.0189
	(2.5)[a]	(7.7)	(3.7)	(-.5)	(4.2)	(1.6)	(3.4)	
Meat	.0090	-.0186	-.0024	.0007	.0043	.0016	.0034	.0020
		(-3.8)	(-1.8)	(.9)	(3.0)	(1.0)	(1.0)	(.3)
Rice	-.0186	.0817	-.0031	-.0026	-.0044	.0058	-.0350	-.0237
	(-3.8)		(-.8)	(-1.1)	(-1.1)	(1.2)	(-2.8)	(-1.2)
Fruits	-.0024	-.0031	.0045	.0001	.0023	-.0047	-.0002	.0036
	(-1.8)	(-.8)		(.1)	(1.9)	(-3.6)	(-.1)	(.7)
Dairy	.0007	-.0026	.0001	.0050	.0018	-.0007	-.0029	-.0014
	(.9)	(-1.1)	(.1)		(2.9)	(-.8)	(-1.7)	(-.5)
Fish	.0043	-.0044	.0023	.0018	.0137	-.0024	.0046	-.0200
	(3.0)	(-1.1)	(1.9)	(2.9)		(-1.8)	(1.2)	(-2.7)
Palawija crops	.0016	.0058	-.0047	-.0007	-.0024	-.0022	-.0056	.0082
	(1.0)	(1.2)	(-3.6)	(-.8)	(-1.8)		(-1.4)	(1.5)
Other Foods	.0034	-.0350	-.0002	-.0029	.0046	-.0056	.0036	.0320
	(1.0)	(-2.8)	(-.1)	(-1.7)	(1.2)	(-1.4)		(1.8)
Non Foods	.0020	-.0237	.0036	-.0014	-.0200	.0082	.0320	-.0008
	(.3)	(-1.2)	(.7)	(-.5)	(-2.7)	(1.5)	(1.8)	
Income	-.0105	-.0748	-.0074	-.0011	-.0298	-.0020	-.0023	.1280
	(-2.7)	(-6.9)	(-2.1)	(-.7)	(-4.3)	(-.6)	(-.2)	
CTMEAT		-190.2	14.1		425.4	-87.8	-235.6	74.0
		(-1.5)	(.4)		(5.8)	(-2.2)	(-1.8)	
CTMILK		-911.8	-560.2		-917.7	-84.8	-1371	3846.2
		(-1.8)	(-3.7)		(-3.1)	(-.5)	(-2.5)	

[a] The numbers in parentheses are asymptotic t-ratios.

Table B-3 Conditional parameter estimates of the AIDS model for the low-income group, share of meats>0, and share of dairy products=0

	Meats	Rice	Fruits	Fish	Palawija crops	Other Foods	Non Foods
Intercept	.0302 (1.7)*	.7644 (12.4)	.0407 (2.8)	.0324 (.9)	.0983 (4.0)	.4501 (6.8)	-.4161
Meat	.0016	-.0035 (-.7)	-.0006 (-.5)	.0045 (3.6)	.0034 (1.8)	-.0010 (-.2)	-.0043 (-.6)
Rice	-.0035 (-.7)	.0488	-.0026 (-.6)	.0014 (.3)	.0003 (.1)	.0370 (2.2)	-.0815 (-3.1)
Fruits	-.0006 (-.5)	-.0026 (-.6)	.0036	.0015 (1.5)	-.0007 (-.5)	.0035 (.8)	-.0046 (-.8)
Fish	.0045 (3.6)	.0014 (.3)	.0015 (1.5)	.0142	-.0021 (-1.2)	.0024 (.6)	-.0219 (-3.3)
Palawija crops	.0034 (1.8)	.0003 (.1)	-.0007 (-.5)	-.0021 (-.5)	-.0098	.0043 (.7)	.0045 (.6)
Other Foods	-.0010 (-.2)	.0370 (2.2)	.0035 (.8)	.0024 (.6)	.0043 (.7)	.0485	-.0947 (-4.0)
Non Foods	-.0043 (-.6)	-.0815 (-3.1)	-.0046 (-.8)	-.0219 (-3.3)	.0045 (.6)	-.0947 (-4.0)	.2025
Income	-.0052 (-1.9)	-.1192 (-10.4)	-.0046 (-1.7)	-.0088 (-1.2)	-.0147 (-3.1)	-.0509 (-4.6)	.2033
CTMEAT		-604.9 (-3.6)	-9.98 (-.3)	196.4 (2.2)	-91.2 (-1.4)	-433.6 (-2.5)	943.1
CTMILK		801.3 (3.1)	53.2 (.9)	186.9 (1.4)	188.0 (1.8)	674.4 (2.4)	-1904

* The numbers in parentheses are asymptotic t-ratios.

Table B-4 Conditional parameter estimates of the AIDS model for the low-income group, share of meats=0, and share of dairy products>0

	Rice	Fruits	Dairy	Fish	Palawija crops	Other Foods	Non Foods
Intercept	.4323	.0008	.0081	.0954	.1318	.3790	-.0474
	(3.3)[a]	(0)	(.5)	(1.6)	(2.2)	(2.8)	
Rice	-.0718	-.0002	-.0070	-.0183	.0228	.0421	.0324
		(-0)	(-1.4)	(-2.0)	(2.1)	(1.7)	(.7)
Fruits	-.0002	-.0017	-.0016	-.0043	-.0043	-.0052	.0174
	(0)		(-1.2)	(-1.7)	(-1.4)	(-.8)	(1.5)
Dairy	-.0070	-.0016	.0093	.0005	.0011	-.0015	-.0009
	(-1.4)	(-1.2)		(.5)	(.8)	(-.4)	(-.1)
Fish	-.0183	-.0043	.0005	.0163	.0029	-.0073	.0102
	(-2.0)	(-1.7)	(.5)		(.7)	(-1.0)	(.7)
Palawija crops	.0228	-.0043	.0011	.0029	-.0141	-.0061	-.0023
	(2.1)	(-1.4)	(.8)	(.7)		(-.7)	(-.1)
Other Foods	.0421	-.0052	-.0015	-.0073	-.0061	.0403	-.0625
	(1.7)	(-.8)	(-.4)	(-1.0)	(-.7)		(-1.7)
Non Foods	.0324	.0174	-.0009	.0102	-.0023	-.0625	.0056
	(.7)	(1.5)	(-.1)	(.7)	(-.1)	(-1.7)	
Income	-.0342	.0046	-.0045	-.0009	-.0292	-.0449	.1090
	(-1.7)	(.8)	(-1.8)	(-.1)	(-2.8)	(-2.4)	
CTMEAT	-123.9	-50.3		-365.5	-1.0	200.0	340.7
	(-.9)	(-1.3)		(-4.1)	(-0)	(1.7)	
CTMILK	112.9	38.0		323.6	64.8	-224.3	-314.9
	(.8)	(.9)		(3.4)	(.8)	(-1.8)	

[a] The numbers in parentheses are asymptotic t-ratios.

Table B-5 Conditional parameter estimates of the AIDS model for the low-income group, share of meats=0, and share of dairy products=0

	Rice	Fruits	Fish	Palawija crops	Other Foods	Non Foods
Intercept	.3016	.0448	.0981	.0038	.3040	.2478
	(2.8)[a]	(2.1)	(2.4)	(.1)	(2.4)	
Rice	.0769	-.0038	.0024	.0178	-.0152	-.0782
		(-.7)	(.4)	(1.9)	(-.6)	(-2.1)
Fruits	-.0038	.0014	.0019	-.0057	.0133	-.0071
	(-.7)		(1.7)	(-3.2)	(2.7)	(-1.1)
Fish	.0024	.0019	.0254	-.0018	.0069	-.0349
	(.4)	(1.7)		(-.7)	(1.3)	(-4.0)
Palawija crops	.0178	-.0057	-.0018	-.0115	-.0153	.0164
	(1.9)	(-3.2)	(-.7)		(-1.9)	(1.4)
Other Foods	-.0152	.0133	.0069	-.0153	.0661	-.0559
	(-.6)	(2.7)	(1.3)	(-1.9)		(-1.7)
Non Foods	-.0782	-.0071	-.0349	.0164	-.0559	.1596
	(-2.1)	(-1.1)	(-4.0)	(1.4)	(-1.7)	
Income	-.0938	-.0007	-.0186	-.0257	-.0468	.1855
	(-5.5)	(-.2)	(-1.9)	(-3.4)	(-3.2)	
CTMEAT	1056.5	-6.7	89.5	593.9	939.8	-2673
	(2.3)	(-.1)	(.4)	(3.0)	(2.0)	
CTMILK	4498.0	-54.8	1866.7	2036.3	3435.9	-11782
	(2.1)	(-.1)	(1.8)	(2.2)	(1.6)	

[a] The numbers in parentheses are asymptotic t-ratios.