Impacts of Income Distribution on Market Demand

By

Diansheng Dong and Oral Capps, Jr

Department of Agricultural Economics
Texas A&M University

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ABSTRACT

This study develops a procedure to estimate income distribution effects on market demand. The proposed procedure contains two steps: estimation of the underlying income distribution and estimation of market demand. Empirical findings show that the income distribution effect is a significant factor in the demand for meat products

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I. Introduction

According to neoclassical theory, consumer demand is a function of consumer tastes, income, and the prices of goods purchased. The market (aggregate) demand for a consumer good is the sum of all consumer demands at given prices in a particular time period. Market demands are often estimated using average consumer income or consumer income from a representative consumer. However, in most cases, the market demand for a good depends on not only the average level of income but also its entire distribution (Gorman; Berndt, Darrough, and Diewert; Jorgenson, Lau, and Stoker). Biased estimates of demand parameters are obtained if market demand functions contain only average consumer income (Muellbauer, 1975, 1976). Examples to address the effect of income distribution on market demand can be found in Blinder; Simmons; and Blundell, Pashardes, and Weber. The most efficient methodology to handle income distribution effects would need panel level data including complete income distribution information (Lewbel, 1989). However, this kind of data is not usually accessible. Seeking an appropriate demand aggregation process accounting for income distribution effects without accessing entire income distribution then becomes valuable.

Market demand is aggregated from its associated individual demands; thus how to specify the individual demand function form becomes essential for any empirical effort trying to address the effects of income distribution. Lewbel (1989) proposed a general demand function at the individual level that nests most demand functions derived from the maximization of utility functions. The corresponding aggregate demand function can be derived from this general individual demand function and can be estimated without distribution information from more than one time period by assuming a “mean scaled” underlying income distribution. However, Lewbel’s procedure may not be applicable broadly. Even if the requirement of complete income distribution data from a given cross-section does not raise any problem, the underlying income distribution may not satisfy the conditions of mean scaling. As Lewbel (1992) defined, the income distribution is mean scaled if and only if, over time, changes in the mean level of income in the economy are independent of changes in inequality measures. Two special cases of mean scaling are “proportional distribution movement” and a log-normal distribution. Lewbel (1992), using annual data published in the U.S. Current Population Reports, Series P-60, rejected mean scaling of the income distribution. Therefore, mean scaling appears to be a strong restriction for income distribution.

In the present approach, we derive the aggregate demand function from a double logarithmic individual demand specification. The double logarithmic functional form is commonly used in demand literature. Lewbel (1992) called this a standard function form for demand models. Examples can be found in Beierlein, Dumn, and McConnon; Houthakker; Halvorsen; and Houthakker, Verleger, and Sheehan.

In next section, we explicitly derive the aggregation bias term which relates to the moment-generating function of the logarithm of the underlying income distribution. The generalized beta distribution of the second kind and the generalized gamma distribution are selected as the underlying income distributions and their associated moment-generating functions are derived. Estimation of the income distribution parameters is discussed in section III. In section IV, we offer an application of the proposed procedure to meat demand. In section V, concluding remarks are made.

II. Modeling Demand Aggregation Bias

Assume that consumer *i*'s demand for good Q at time *t* can be written as follows:

(1) $$\ln Q_{it} = \alpha_0 + \alpha_1 \ln P_{1t} + \cdots + \alpha_m \ln P_{mt} + \alpha_y \ln Y_{it},$$

where the subscript i refers to the *i*th consumer; $P_1, \ldots, P_m$ are the prices of the various goods in the demand specification; Y_i is the income of consumer i; and $\alpha_1, \ldots, \alpha_m$ are the price elasticities and α_y is the income elasticity of demand, respectively. If we also assume that all consumers have identical demand functions and face identical prices, but we allow for different incomes, the average quantity demanded by all consumers in the market can be expressed as:

(2) $$\ln Q_t = \alpha_0 + \alpha_1 \ln P_{1t} + \cdots + \alpha_m \ln P_{mt} + \ln(\frac{1}{n}\sum_{i=1}^{n} \exp(\alpha_y \ln Y_{it})),$$

where $Q_t = \frac{1}{n}\sum_{i=1}^{n} Q_{it}$ is the average consumption of good Q at time *t* and n is the total number of consumers. From equation (2), the average consumption of good Q at time *t* is a function of prices of goods 1 through m and of all consumer incomes Y_{it} at time *t*, i=1, 2, ..., n. To estimate equation (2) with aggregate time-series data, a series of observations on the income of each consumer would be needed. This result implies that the distribution of income would affect average market demand. In most empirical studies using the double logarithmic specification, the estimated market average demand function is defined as:

(3) $$\ln Q_t = \alpha_0 + \alpha_1 \ln P_{1t} + \cdots + \alpha_m \ln P_{mt} + \alpha_y \ln \overline{Y}_t,$$

where $\overline{Y}_t = \frac{1}{n}\sum_{i=1}^{n} Y_{it}$, the mean income of all consumers.

Equation (2) equals equation (3) when the following equality holds:

(4) $$\frac{1}{n}\sum_{i=1}^{n} \exp(\alpha_y \ln Y_{it}) = \exp(\alpha_y \ln \overline{Y}_t).$$

Equality (4) holds if any one of the following three conditions is satisfied: (i) the income elasticity of demand for good Q is exactly 1; (ii) the income elasticity is exactly 0; or (iii) all consumers have the same income (Hahn, 1988). Lewbel (1992) proved that if the underlying income distribution is mean scaled, demand elasticities in equation (1) can be consistently estimated using equation (3); thus equation (4) holds under the condition of mean scaling.

If none of these conditions is met, replacing the left side of equation (4) with the right side, when market demands are estimated, can lead to aggregation bias. However, as we mentioned above, to estimate equation (2) instead of (3) one would need a series of observations on the income of each consumer for each time period. In most cases, this data requirement is not attainable. Thus the issue arises of how to eliminate potential aggregation bias without retrieving information on individual incomes of all consumers.

The left-hand side of equation (4), as showed by Hahn (1988), is the empirical moment-generating function of ln*Y* evaluated at α_y. In fact, when $n \to \infty$, we have

(5) $$\frac{1}{n}\sum_{i=1}^{n} \exp(\alpha_y \ln Y_{it}) = E[\exp(\alpha_y \ln Y_t)] = M_{\ln Y_t}(\alpha_y),$$

where $E[\cdot]$ is the expectation operator, and $M_{\ln Y_t}(\alpha_y)$ represents the moment-generating function of $\ln Y_t$ evaluated at α_y.Given (5), equation (2) can be expressed as

(6) $$\ln Q_t = \alpha_0 + \alpha_1 \ln P_{1t} + \cdots + \alpha_m \ln P_{mt} + \ln M_{\ln Y_t}(\alpha_y).$$

If the underlying income distribution is known, in most cases, $M_{\ln Y_t}(\alpha_y)$, the moment-generating function, can be derived.

In the literature, many distributions have been considered as descriptive models for the distribution of income, such as Pareto (Mandelbrot); Weibull (Bartels and van Metelen); lognormal (Aitchison and Brown); Singh-Maddala (Singh and Maddala); Gamma (Salem and Mount) and Beta (Kakwani and Podder). McDonald discussed and compared some of the aforementioned distributions and favored the generalized beta distribution of the second kind (GB2) which nests most of the other income distributions. The pdf of the GB2 is defined as

(7) $$f(Y;a,b,c,d) = \frac{aY^{ac-1}}{b^{ac}B(c,d)(1+(Y/b)^a)^{c+d}}, \qquad Y \geq 0,$$

where a, b, c ,d are parameters, all of which must be greater than 0, and $B(c,d) = \Gamma(c)\Gamma(d)/\Gamma(c+d)$, is the beta function. The moment-generating function of ln*Y* evaluated at α_y for the GB2 distribution can be derived as follows:

(8) $$\begin{aligned} M_{\ln Y}(\alpha_y) &= E[\exp(\alpha_y \ln Y)] \\ &= E[Y^{\alpha_y}] \\ &= \int_0^{+\infty} \frac{aY^{ac+\alpha_y-1}}{b^{ac}B(c,d)(1+(Y/b)^a)^{c+d}}\,dY \\ &= \frac{b^{\alpha_y}\Gamma(c+\alpha_y/a)\Gamma(d-\alpha_y/a)}{\Gamma(c)\Gamma(d)}. \end{aligned}$$

In fact, $M_{\ln Y}(\alpha_y) = E[Y^{\alpha_y}]$, is the α_y th moment of *Y*. When α_y =1, equation (8) is

$$M_{\ln Y}(1) = E[Y] = \frac{b\Gamma(c+1/a)\Gamma(d-1/a)}{\Gamma(c)\Gamma(d)},$$

the mean of *Y* under the GB2 distribution. In this case, the first condition of equation (4) holds and mean income fully represents the effect of income distribution. Similarly, if α_y =0, the second condition holds, we have $M_{\ln Y}(0) = 1$, indicating that income has no role in the aggregate demand given by equation (6).

For purposes of comparison, the generalized gamma income distribution also is considered in this study. The pdf of generalized gamma (GG) is given by

$$g(Y;a,b,c) = \frac{aY^{ac-1}e^{-(Y/b)^a}}{b^{ac}\Gamma(c)}, \qquad Y \geq 0,$$

where a, b, c are all positive parameters and $\Gamma(\cdot)$ denotes the gamma function. The associated moment-generating function of GG can be derived as

$$M_{\ln Y}(\alpha_y) = \frac{b^{\alpha_y}\Gamma(c+\alpha_y/a)}{\Gamma(c)}.$$

III. Estimation of Income Distributions

To estimate equation (6), one must first estimate the parameters of the income distribution. A number of procedures for estimating the income distributions have been presented in the literature. Most of the estimation methods are based upon census data relating to the proportion of persons in various income categories. Examples can be found in Dagum; McDonald and Ransom; McDonald; Majumder and Chakravarty; and Mittelhammer, Shi, and Wahl.

The parameters a, b, c, d, in equations (7) or (8), in this analysis, are estimated using the minimum chi-square method. That is, the parameters are estimating based on minimized the following chi-square statistic:

(9) $$\chi^2 = n\sum_{k=1}^{K}\frac{(n_k / n - F_k(\Theta))^2}{F_k(\Theta)},$$

where $\Theta = a, b, c, d$ and K is the number of income categories; n_k is the number of observations in category k, $n = \sum_{k=1}^{K} n_k$ is the sample size.

(10) $$F_k(\Theta) = \int_{Y_{k-1}}^{Y_k} f(Y;\Theta)dY$$

is the predicted proportion of the population or relative frequencies in the kth income group (*k=1,...,K*), and the n_k / n corresponds to the observed relative frequencies associated with the kth income group[1].

To estimate the parameters of the GB2 and GG distributions, data from *Current Population Reports: Consumer Income* published by the U.S. Bureau of Census, covering the years 1970 through 1992, were used. Data beyond 1992 were not available. Minimization of the chi-square statistic given in (9) was accomplished using the GAUSS program.

The estimated parameters for the income distributions are reported in tables 1 and 2. The last three columns in tables 1 and 2 correspond to goodness-of-fit measures, namely the sum of squared errors, the sum of absolute errors, and the mean absolute percent errors. The estimated parameters of the income distributions are not constant over time. The estimated income distributions fit the observed personal income distribution data quite well as evident from the goodness-of-fit measures. For the GB2 income distribution, the mean absolute percent error varies from 2.76 percent to 9.32 percent. Similarly for the generalized gamma distribution, the mean absolute percent error varies from 6.34 to 11.80 percent

As Lewbel (1992) point out, if the underlying income distribution is mean scaled, unbiased estimates can be obtained by estimating equation (3) directly. Thus, it is necessary to test the income data for mean scaling. The testing procedure proposed by Lewbel (1992, *Property* 5, pp639) is used in this study. For perfect mean scaling income distribution, the correlation coefficients between mean and inequality measurement is zero. The higher the correlation coefficient, the higher probability to reject mean scaling. For the annual data from 1970 to 1992, we find the correlation coefficients ranged from 0.82 to 0.98; consequently, we strongly reject the mean scaling hypothesis for these income data.

IV. Empirical Application

In this section, demand functions for beef, pork, and poultry are estimated using equation (6). The aggregate time-series data of per capita annual consumption and real price indices are derived from *Food Consumption, Prices, and Expenditures, 1996, Annual data, 1970-1994* by United States Department of Agriculture. The series of income distribution parameters obtained in the previous section associated with each year are treated as given exogenous variables. In this application, equation (6) is augmented by accounting for potential taste/structural change effects. A quadratic time trend specification was used to capture trends in consumption. A structural break in consumer preferences was considered by a time dummy variable, dm_t. The Akaike Information Criterion (AIC) was used to choose among all possible time frames corresponding to dm_t.

In addition, an interaction term of time trend with dm_t, also is included in equation (6) “for modeling a possible change in taste-induced consumption trends caused by a structural break in preferences” (Mittelhammer, Shi, and Wahl, pp. 255). Because of the nonlinearity in parameters due to the term $\ln M_{\ln Y_t}(\alpha_y)$, a non-linear estimation procedure was used. Comparisons to equation (6), augmented by the use of the structural change terms, are made with with the conventional specification of the demand function given by equation (3).

The estimated demand parameters are provided in Table 3. Estimates are quite consistent among models. In the two income distribution models, parameters estimated are almost identical. Own-price elasticities in all the models are negative, inelastic, and statistically significant. The income elasticities are positive, and less than 1, indicative of normal goods, but significant only for beef and poultry. The time dummy variable, dm_t, is the same for all the commodities, 1 for 1976 and beyond and 0 otherwise. The time trend variable starts at 1 in 1970 and advances 1 each time period. At least one of the four time trend and dummy variables significantly affected the demand responses in all models. Consistent with previous studies, the taste/structural changes play a role in aggregate demand analysis. In this study, the interaction term of the time dummy and trend revealed that, after 1976, time trend has been accelerating the decrease in beef consumption and the increase in poultry, but there was no significant effect on pork. However, the overall trend did have a significant negative effect on pork consumption.

Parameter value differences between the GB2 model and conventional models ranged from as little as 0.86% to a high of 471.43% with a mean absolute percent difference of 41.69%. But the differences among corresponding significant variables are quite small and within 10% except for the trend-squared variable in poultry equation which is 28.57%. The mean absolute percent difference of significant variables is 6.84%. Analogous results in parameter value differences between the GG and conventional models can also be calculated.

The three own-price elasticities in the conventional model specification were *over* estimated by about 3%, and all three income elasticities were *under* estimated on average by about 12%, not much of difference for both. Hence the effect of income distribution on estimates of aggregate demand parameters is “moderate but notable” as described by Mittelhammer, Shi, and Wahl (1996).

One argument for not correcting for aggregation bias is that the taste/structural change variables are proxies for the aggregation bias correction terms. Own-price, cross-price and income elasticity estimates without the aggregation bias correction in the conventional model are similar to those derived from models with the aggregation bias correction. Reestimation of bias-corrected models without the taste/structural change variables yielded notable changes in demand parameter estimates. These results may imply that the taste/structural change variables can proxy aggregation bias correction terms to some degree, but not vice versa. This result is consistent with Buse’s findings as he concluded (p. 52):

> “It can also be argued that the distribution variables are simply picking up simple time trends due to the trending character of the distribution proportions. However, the argument can be placed on its head and one can argue with equal justification that the time trends, if used in lieu of the distribution variables, would pick up the effect of the relevant and omitted distribution effects...In most cases the trend specification is significant and uniformly so whenever the distribution variables are included in the specification.

> Thus, the trend terms make an independent contribution over and above that captured by the distributional variables."

Even so, one cannot rely on the taste/structural change variables fully representing the income distribution effects (Mittelhammer, Shi, and Wahl). Therefore, success to segregate income distribution effects from taste/structural change effects relies, in some degree, on the accuracy of the functional presentation of aggregate taste effects.

V. Concluding Remarks

We developed a simple, but useful approach to account for income distribution effects for a double logarithmic (non-linear) market demand specification. The aggregation bias correction term relates to the moment-generating function of the logarithm of the underlying income distribution. Various income distributions have been discussed in literature and their estimation is straightforward given information from the U.S. Bureau of the Census. This information also is readily available in most developed countries.

Empirical findings of the meat commodities in this study suggest that the income distribution effects are important and significant. In fact, the own-price elasticities were over-estimated and the income elasticities were under estimated when income distribution effects were not properly taken into account. The magnitude of effects was moderate consistent with the findings of other studies. Further research on other commodities, both food and nonfood groups, is needed to generalize the results.

Footnotes:

McDonald and Ransom discussed the superiority of this grouped data estimation procedure as compared to other alternative procedures. However, McDonald (1984) used the approach of maximizing the multinomial likelihood function and claimed that the resulting estimators are asymptotically efficient relative to other estimators based on grouped data. The associated multinomial likelihood function can be expressed as:

$$L(\Theta) = n! \prod_{k=1}^{K} \frac{(F_k(\Theta))^{n_k}}{n_k!}$$

Both of the two methods were used in this study and no notable differences in parameter estimates were evident. Thus only the results using the minimum chi-square method are reported in this paper.

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Table 1. Estimated Parameters of GB2 Income Distribution

year	*a*	*b*	*c*	*d*	predicted mean	actual mean	X^2 ($X10^6$)	SSE	SAE	MAPE (%)
1970	2.757078	40148.60	0.2591048	1.463810	17796	18132	0.625377	0.000462	0.051560	6.73
1971	2.187596	47114.55	0.351459	2.208952	17821	18270	1.031459	0.000731	0.062659	9.04
1972	2.118837	49205.37	0.3701838	2.251374	18737	19294	1.084361	0.000822	0.071192	9.32
1973	1.626785	80107.15	0.5135495	4.729651	18816	19451	0.516689	0.000421	0.048199	6.08
1974	1.768482	58907.43	0.4771448	3.275363	18454	18952	0.415205	0.000330	0.044269	5.65
1975	1.708958	61597.73	0.5086577	3.713424	17972	18650	0.376452	0.000293	0.040654	5.33
1976	1.672162	65919.43	0.5187545	3.966519	18251	18943	0.391774	0.000291	0.041729	5.46
1977	1.797676	53246.60	0.4825688	2.890152	18672	19262	0.427226	0.000313	0.042716	5.50
1978	2.045189	48803.14	0.3903029	2.284248	18749	19447	0.144236	0.000116	0.024291	2.80
1979	2.927016	36311.91	0.2488632	1.136299	18801	19279	0.346391	0.000276	0.035487	4.08
1980	2.474802	41202.11	0.3081628	1.613235	18540	18847	0.318552	0.000258	0.037637	4.31
1981	2.543230	38506.04	0.3003636	1.479706	18217	18650	0.318118	0.000252	0.034640	4.04
1982	2.365261	39513.50	0.3267622	1.587762	18427	18767	0.261390	0.000206	0.032188	3.51
1983	2.260494	43338.24	0.3442986	1.812935	18774	19073	0.347986	0.000275	0.038271	4.18
1984	2.025818	48944.57	0.3995176	2.263040	19154	19595	0.383014	0.000305	0.040351	4.25
1985	2.089909	47007.25	0.3893892	2.052896	19666	20096	0.278472	0.000220	0.034109	3.57
1986	2.175428	46394.62	0.3733667	1.887060	20361	20842	0.412406	0.000315	0.040035	4.13
1987	2.176322	45072.98	0.3810554	1.837675	20457	21203	0.251138	0.000185	0.031071	3.20
1988	2.391744	41141.16	0.3476514	1.504074	20879	21563	0.328930	0.000239	0.034704	3.63
1989	2.374889	39340.82	0.3614779	1.418138	21385	22047	0.193199	0.000138	0.026320	2.76
1990	2.458821	38092.53	0.3511001	1.362759	21056	21444	0.300149	0.000211	0.030992	3.30
1991	2.218641	38624.72	0.4056423	1.566917	20749	21023	0.408400	0.000291	0.039606	4.21
1992	2.137900	41517.44	0.4169660	1.725351	20912	21024	0.483040	0.000345	0.042522	4.45

Notes: X^2 is defined by equation (9) evaluated at $\hat{\Theta}$. SSE= $\sum_{k=1}^{K}(\frac{n_k}{n} - F_k(\hat{\Theta}))^2$, SAE= $\sum_{k=1}^{K}\left|\frac{n_k}{n} - F_k(\hat{\Theta})\right|$ and MAPE= $\frac{1}{K}\sum_{k=1}^{K}\left|(\frac{n_k}{n} - F_k(\hat{\Theta})) / (\frac{n_k}{n})\right| \times 100\%$ are the sum of squared errors, sum of absolute errors and mean absolute percent errors respectively. Income categories used for all years are defined by the followings:

(1) \$0 to \$2,499; (2) \$2,500 to \$4,999; (3) \$5,000 to \$\$9,999; (4) \$10,000 to \$14,999;

(5) \$15,000 to \$24,999; (6) \$25,000 to \$49,999; (7) \$50,000 to \$74,999; (8) > \$75,000.

The income figures are in real terms, 1992 dollars.

Table 2. Estimated Parameters of Generalized Gamma Income Distribution

year	*a*	*b*	*c*	predicted mean	actual mean	X^2 ($X10^6$)	SSE	SAE	MAPE (%)
1970	1.338340	29682.74	0.6002966	17776	18132	1.060253	0.000596	0.059185	10.93
1971	1.236772	26242.42	0.6956826	17825	18270	1.273229	0.000724	0.065500	11.80
1972	1.214679	26668.62	0.7206058	18707	19294	1.307198	0.000798	0.060316	10.62
1973	1.186334	25699.34	0.7533654	18798	19451	0.591382	0.000375	0.040826	6.65
1974	1.143150	23426.53	0.8112865	18429	18952	0.582635	0.000286	0.035135	6.88
1975	1.137688	22161.93	0.8372477	17964	18650	0.530864	0.000250	0.036731	7.11
1976	1.139612	22698.07	0.8296058	18238	18943	0.521753	0.000255	0.034097	6.52
1977	1.095730	21643.73	0.8847576	18630	19262	0.647547	0.000306	0.040371	7.53
1978	1.195360	25980.70	0.7395556	18676	19447	0.452620	0.000201	0.035755	6.34
1979	1.255693	28708.79	0.6614516	18646	19279	1.163224	0.000557	0.059687	10.33
1980	1.264092	27926.42	0.6751939	18469	18847	0.881228	0.000381	0.049950	9.10
1981	1.228121	26390.14	0.7048975	18141	18650	0.993004	0.000454	0.054800	9.76
1982	1.183054	25479.62	0.7385783	18311	18767	0.901937	0.000400	0.048172	8.73
1983	1.210488	26695.45	0.7183591	18677	19073	0.839717	0.000383	0.050236	8.47
1984	1.183237	25953.36	0.7565723	19063	19595	0.739173	0.000351	0.043712	7.32
1985	1.173848	26101.62	0.7717989	19539	20096	0.676494	0.000315	0.046095	7.24
1986	1.194023	27521.40	0.7566198	20196	20842	0.846290	0.000426	0.054260	7.93
1987	1.172607	26500.93	0.7904149	20275	21203	0.733277	0.000332	0.044627	7.08
1988	1.173796	26636.59	0.8018306	20643	21563	0.975774	0.000457	0.055116	8.38
1989	1.113446	24582.90	0.8844249	21068	22047	0.935061	0.000402	0.046457	7.69
1990	1.118809	24103.99	0.8908679	20773	21444	1.114163	0.000522	0.056851	8.78
1991	1.046023	20821.95	1.0024220	20499	21023	1.151891	0.000494	0.052729	8.76
1992	1.072363	22236.33	0.9536407	20683	21024	1.106381	0.000479	0.052012	8.43

Notes: X^2 is defined by equation (9) evaluated at $\hat{\Theta}$. SSE= $\sum_{k=1}^{K}(\frac{n_k}{n} - F_k(\hat{\Theta}))^2$, SAE= $\sum_{k=1}^{K}\left|\frac{n_k}{n} - F_k(\hat{\Theta})\right|$ and MAPE= $\frac{1}{K}\sum_{k=1}^{K}\left|(\frac{n_k}{n} - F_k(\hat{\Theta}))/(\frac{n_k}{n})\right| \times 100\%$ are the sum of squared errors, sum of absolute errors and mean absolute percent errors respectively. Income categories used for all years are defined by the followings:

(1) $0 to $2,499; (2) $2,500 to $4,999; (3) $5,000 to $$9,999; (4) $10,000 to $14,999;

(5) $15,000 to $24,999; (6) $25,000 to $49,999; (7) $50,000 to $74,999; (8) > $75,000.

The income figures are in real terms, 1992 dollars.

Table 3. Demand Parameter Estimates for Models of GB2 and Generalized Gamma (GG) and the Conventional Model without the Aggregation Bias

	I. GB2 Model		II. GG Model		III. Conventional Model	
Variables	Parameter	t-value	Paramete	t-value	Parameter	t-value
Beef equation:						
Intercept	3.5758	2.653	3.4875	1.623	4.2081	2.971
$\ln(P_{beef})$	-0.5165	-12.487	-0.5184	-10.818	-0.5332	-10.43
$\ln(P_{pork})$	0.0962	1.773	0.0969	1.633	0.0828	1.288
$\ln(P_{poultry})$	-0.0618	-0.804	-0.0604	-0.650	-0.0425	-0.472
α_y (Income elasticity)	0.3290	2.171	0.3377	1.409	0.2564	1.610
Dm_{1976}	0.2722	5.383	0.2726	5.226	0.2949	4.914
Trend	0.0068	1.895	0.0070	1.788	0.0079	1.818
$Trend^2$	0.0002	0.780	0.0002	0.769	0.0003	1.309
Dm_{1976} X Trend	-0.0395	-4.836	-0.0397	-4.810	-0.0436	-4.521
Pork equation:						
Intercept	4.1288	2.231	4.0648	2.202	4.1667	2.117
$\ln(P_{beef})$	0.4652	7.526	0.4638	7.832	0.4555	6.412
$\ln(P_{pork})$	-0.7587	-10.518	-0.7581	-10.198	-0.7653	-8.570
$\ln(P_{poultry})$	-0.0040	-0.037	-0.0037	-0.035	-0.0007	-0.006
α_y(Income elasticity)	0.1280	0.612	0.1349	0.644	0.1232	0.556
Dm_{1976}	0.0707	1.086	0.0713	1.127	0.0897	1.075
Trend	-0.0149	-2.993	-0.0147	-2.959	-0.0140	-2.324
$Trend^2$	0.0005	1.893	0.0005	1.940	0.0006	1.867
Dm_{1976} X Trend	-0.0047	-0.455	-0.0048	-0.482	-0.0081	-0.601
Poultry equation:						
Intercept	-1.1477	-1.070	-1.2399	-1.225	-0.9844	-0.963
$\ln(P_{beef})$	0.2612	8.147	0.2600	7.734	0.2588	7.011
$\ln(P_{pork})$	-0.0127	-0.316	-0.0119	-0.289	-0.0281	-0.601
$\ln(P_{poultry})$	-0.2409	-4.342	-0.2384	-4.420	-0.2538	-3.902
α_y (Income elasticity)	0.4926	4.139	0.5007	4.513	0.4768	4.146
Dm_{1976}	-0.0463	-1.180	-0.0470	-1.191	-0.0144	-0.333
Trend	-0.0116	-4.174	-0.0114	-4.105	-0.0110	-3.523
$Trend^2$	0.0007	4.936	0.0007	4.669	0.0009	5.442
Dm_{1976} X Trend	0.0165	2.586	0.0165	2.633	0.0109	1.564
R^2:						
Beef		0.986		0.986		0.986
Pork		0.952		0.952		0.952
Poultry		0.998		0.998		0.998
Durbin-Watson:						
Beef		2.198		2.200		2.232
Pork		2.491		2.492		2.530
Poultry		1.858		1.858		1.811