A Reassessment of Product Aggregation Bias in Demand Analysis: An Application to the U.S. Meat Market

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Abstract
This article reports tests of aggregation over elementary beef, pork, and chicken products in the U.S. and proposes a simple procedure for controlling product aggregation bias in demand estimation. Previous empirical aggregation tests restrict attention to time series residual-based unit root and cointegration tests, which are known to have low statistical power and are subject to normalization problems. Because economic time series are usually short, we apply a panel Generalized Composite Commodity Theorem test with higher power in order to draw sharper inferences. Considering the strategic nature of price formation, there is a close relationship between product aggregation bias and price endogeneity in demand analysis, which we illustrate using an application to the U.S. meat market. Results from two estimated flexible demand systems suggest that product aggregation bias could be reduced significantly by instrumental variables. This finding provides another justification for checking price endogeneity when proper instruments are available.

1. Introduction

Although demand analysis is one of the most studied issues in the agricultural economics literature, most empirical studies of food demand focus on highly aggregated product groups partly for convenience and partly due to lack of data at more disaggregated levels. When more detailed information such as barcode-level scanner data is available, one has the option to rely on product aggregation theories to determine how best to aggregate elementary products into product groups whose demand can be estimated. Some level of product aggregation is necessary for estimating continuous flexible demand systems because of price multicollinearity and curse of dimensionality of the parameter vector. Proper product aggregation reduces bias in the elasticity estimates while incorrect aggregation may introduce large errors to the empirical results.

The interest in proper product aggregation is not new. A number of studies have applied the Generalized Composite Commodity Theorem (GCCT) of Lewbel (1996) to test for aggregation of food products (e.g., Asche et al., 1999; Capps and Love, 2002; Eales et al., 1998; Karagiannis and Mergos, 2002; Reed et al., 2003; Reed et al., 2005; Schulz et al., 2002) or agricultural supplies (Davis et al., 2000; Williams and Shumway, 2000). The GCCT abandons the conventional separability requirement for consistent product aggregation and relies on empirically more plausible assumptions on price movement. Therefore, a test of the GCCT involves unit root and cointegration tests of the price series. As all previous empirical examinations of the GCCT employ time series data, a potential limitation with existing studies is the low power in unit root and cointegration tests based on short time series data.

In addition, there is a close relationship between product aggregation bias and price endogeneity in demand analysis. A price endogeneity problem can arise in the estimation of aggregate demand functions when the price determination process involves significant interplay of supply and demand. Econometrically, this implies estimates of demand parameters are biased and inconsistent. Whenever there are factors affecting consumer behavior that are not accounted for by the econometrician, such endogeneity issues are likely to arise (Dhar et al., 2003).

There are at least two ways in which incorrect product aggregation may cause price endogeneity. First, one common justification for treating prices as exogeneous is based on the assumption that consumers are price takers and, therefore, have no influence on retail prices. While this may be true at the disaggregated, such as brand or barcode, level, it is less tenable at the more aggregated product group level. Second, aggregation bias in demand system can be considered as an “omitted-variables” problem (Davis, 1997; Shumway et al., 2001), the “measured aggregation bias” variable is lost in the demand equations. As such, endogeneity comes from an omitted confounding variable which is correlated with the price variables and the error term.

In this study, we will illustrate the relationship between aggregation bias and price endogeneity through a case study of the U.S. meat market. After correcting price endogeneity by instrumental variables, we find that the aggregation bias in elasticity estimates could be reduced significantly. This is good news for practitioners of demand system models whenever instrumental variables are available. We make the following two contributions to the empirical literature on product aggregation and demand analysis.

First, this is the first application of a panel GCCT test. Consequently, the power of the empirical test is significantly greater than that of the standard time-series unit root tests and cointegration tests adopted in previous GCCT literature (Asche et al., 1999; Reed et al., 2005; Schulz, Schroeder, and Xia, 2012). In general, unit root tests have low statistical power in short time series data. The augmented Dickey–Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests used in previous literature have very low power against *I(0)* alternatives that are close to being *I(1)*. That is, unit root tests cannot distinguish highly persistent stationary processes from nonstationary processes very well, especially for a short-length time series. Thus, the stationarity properties of the data could be seriously misguided. This might be the main reason why previous researchers surprisingly found deflated log-mean group prices to be nonstationary, contrary to common economic sense (Lewbel, 1996, Reed et al., 2005, Schulz, Schroeder, and Xia, 2012). The Engle-Granger cointegration test has similar size and power problems to those of the ADF and KPSS tests. Therefore, most of the deflated group price indices and relative elementary prices were surprisingly nonstationary and not cointegrated. We address the power issue using panel unit root tests. The spatial variation across markets adds a great deal of new information to temporal variation in the time series prices, resulting in potentially more precise parameter estimates (Taylor and Sarno, 1998). Second, we evaluated the degree of bias resulting from inconsistent product aggregation and proposed using instrumental variables to control for this bias. We showed that a significant portion of the aggregation bias is removed by use of instrumental variables.

The remainder of this paper is organized as follows. Section 2 reviews the literature, which is followed by a description of the data in section 3. Our empirical strategy is detailed in section 4. Sections 5 and 6 present the results and robustness test, respectively. The final section concludes.

2. Literature Review

Testing product aggregation is complex and evolving as aggregation theories emerge and change over time. As the literature has grown, so has debates about how to measure and control for aggregation bias in demand estimation. Studies that most closely relates to ours are Nayga and Capps (1994), Eales and Unnevehr (1988), Davis. (1997), Shumway and Davis (2001), Reed et al. (2005), and Schulz et al. (2012). Nayga and Capps (1994) conducted parametric tests of weak separability among twenty-one disaggregated meat products. Four partitions of meat products are examined, and the hypothesis of weak separability is rejected. Eales and Unnevehr (1988) estimated dynamic almost ideal demand systems for meat aggregates and for disaggregated meat products. Tests for weak separability show that consumers choose among meat products rather than meat aggregates. Therefore, tests for structural change in the meat aggregates may be biased. Davis (1997) develops a simple procedure for incorporating product aggregation bias in demand system that permits testing of product aggregation bias with a likelihood ratio test. Shumway and Davis (2001) identified 22 empirical studies that tested for consistent aggregation of food or agricultural commodities. They find that failure to reject consistent aggregation in a partition did not eliminate erroneous inference due to aggregation. Reed et al. (2005) reported tests of aggregation over food products and estimates of aggregated food demand elasticities. They observed that food prices follow a unit root process, which led them to simplify existing tests of GCCT. Finally, Schulz et al. (2012) reported tests of aggregation over elementary ground beef products differentiated by fat content and brand, and estimated composite demand elasticities. We build on this line of research by simultaneously examining multiple meat species, conducting panel GCCT tests, controlling for price endogeneity, and employing alternative demand functional forms to improve robustness of the results. No previous research contains all these features in a single study.

3. Data and Construction of Variables

Meat sales data come from the IRI InfoScan retail scanner data that the USDA Economic Research Service acquired to support its food market and policy research (Muth et al., 2016). Our sample covers 65 quadweeks (i.e., 4-weekly periods) between January 6, 2008, and December 29, 2012. In InfoScan, there are 65 markets and 8 standard whitespaces (i.e., remaining areas). We dropped the markets from the sample if there is missing meat sales data to construct a balanced panel. We aggregated barcode-level sales data by product attributes to form unique elementary products. The final products included in our study accounted for 90.5%, 99.87% and 92.42% of total sales of beef, pork and chicken in InfoScan. Some retailers provided data at the store level but others only at the Retail Market Area (RMA) level. The exact RMA definition varies from one retailer to another but a typical RMA contains a cluster of counties. We aggregate store-level data to the IRI market level. For RMA-only retailers, IRI reports the number of stores and addresses under each RMA. To impute IRI market-level sales for these retailers, we divided RMA-level sales by store number to get average sales per store and allocate RMA sales to each IRI market based on the number of stores the retailer has in each IRI market.

For policy analysis, it is important to include a *numéraire* good in the demand system to account for substitutions between meats and all other goods and services. To back out a price for the *numéraire*, let EXP_{mt} denote total household income for market *m* in period *t*, and w_{mit} the expenditure share of meat category i. Following Wohlgenant (1989), the price index for the *numéraire* good J is obtained by solving

$$(1)\quad \ln EXP_{mt} = \sum_{j=1}^{J} w_{mjt} lnp_{mjt}$$

for lnp_{mJt}. To reduce the unit value bias (Deaton 1988; Cox and Wohlgenant, 1986), we created a superlative Törnqvist price index for each meat category. This feature allows us to account for within-category product substitution without explicitly estimating a product-level demand model. To simplify notation for panel price comparisons, let an entity be a unique combination of location and time. For example, the same location (e.g., a county) in period t and period t+1 is considered two distinct entities in our index formulas. The Törnqvist price index is calculated as

(2) $p_T^{0j} = exp\{0.5 \sum_{v \in 0j} (s_v^0 + s_v^j) ln(p_v^j / p_v^0)\}$

where p_v^j is the is the price of product v in entity j; p_v^0 and q_v^0 are the base price and quantity of product v, respectively; and v_{0j} demotes the common set of items sold in both base *0* and entity j. s_v^0 and s_v^j are budget shares of product v in base *0* and entity j, respectively.

The instrumental variable for each product-level price index is calculated as the weighted average of the price index values of the same product in all other IRI markets within 300 miles. The inverse of the Euclidian distance between the target market and other markets is used as weight. The concept of using prices of adjacent locations to instrument endogenous prices originated from Hausman (1997). The identifying assumption is that after controlling for mean market valuations of products and market fixed effects, market-specific demand shocks and measurement errors are independent across markets. This type of instrument is useful in overcoming endogeneity bias when researchers lack supply-side variables that possess the degree of specificity required to identify variation in relative prices of highly disaggregated goods.

4. Empirical Strategy

We begin this section with a brief introduction to GCCT and the two demand system models we use.

4.1 Generalized Composite Commodity Theorem

Prior to Lewbel's invention of GCCT, there were two approaches to testing product aggregation. First, separability is sufficient for testing commodity-wise aggregation (Deaton and Muellbauer, 1980). Separable preferences reveal the way in which consumers prefer to aggregate because their aggregation scheme is embedded in the structure of their utility functions. Separable preferences restrict the patterns of expenditures and test how consumers allocate their expenditures over groups of products. The problem with this approach is that because the utility function restricts substitution patterns, aggregation tests based on separability are often rejected empirically (Eales and Unnevehr, 1988; Nayga and Capps, 1994; Diewart and Wales, 1995). The second approach is to appeal to the Composite Commodity Theorem (CCT; Hicks, 1939; Leontief, 1936). Instead of restricting utility functions, the CCT restricts price movement. The limitation of the CCT approach is that consistent aggregation requires relative prices within a group to be constant over time. This empirically implausible requirement results in frequent rejection of CCT-based aggregation schemes.

In a seminal study, Lewbel (1996) argues that commodity aggregation can be justified by relaxing the restrictive requirements implied by separable preferences and constant relative prices. The new theory, called GCCT, only requires that relative elementary prices be statistically independent of the group-level prices as opposed to being strictly constant over time. This restriction generally concurs with the widely-observed price multicollinearity among similar elementary goods. Aggregability only requires that changes in relative prices of elementary goods within a group be unrelated to the overall rate of inflation of the group (Lewbel, 1996).

Following Lewbel (1996), the GCCT maintains that n elementary share equations are functions of logged elementary prices, r, and logged income, z. Let w_i (i =1, …… , n) denote the budget share of i_{th} elementary product. Then an elementary good's budget share w_i is defined to comprise a Marshallian demand function $g_i(r,z)$ plus an error term e_i with a conditional mean zero such that,

(3) $w_i = g_i(r,z) + e_i$

where $E(e_i|r,z) = 0$ and $g_i(r,z) = E(w_i|r,z)$. Because the budget share function forms a valid demand system, they also satisfy adding-up ($\sum g_i = 1$), homogeneity ($g_i(r-z, z-k) = g_i(r,z)$ for all i), and symmetry ($\left(\partial g_h/\partial r_j\right) + (\partial g_k/\partial z)g_j = (\partial g_j/\partial r_k) + (\partial g_j/\partial z)g_k$). The compensated demand satisfies negative semi-definiteness.

The theory also maintains the existence of a system of aggregate, or composite, share equations. The $N(< n)$ composite shares $W_I = \sum_{i\in I} w_i(I = 1, \dots\dots, N)$ are functions of logged composite process, R and logged income, z. Specifically,

(4) $W_I = G_I(R,z) + \varepsilon_I$

where $E(\varepsilon_i|R,z) = 0$ and $G_I(R,z) = E(W_I|R,z)$. Following Lewbel (1996), let $G_I^*(r,z) = \sum_{i\in I} g_i(r,z)$. Also define $\rho_i = \gamma_i - R_I$ as the i_{th} relative price so the vector of all relative prices is $\rho = r - R^*$ where R^* denotes the *n*-vector of group prices with R_I in row i and I every row $i \in I$. Lewbel (1996) demonstrates that valid aggregation is obtained when the vector of all relative prices, ρ, is statistically independent of composite prices, R, and income, z. This implies,

(5) $\int G_I^*(R^* + \rho, z)dF(\rho) = E[G_I^*(R^* + \rho, z)|R, z] = G_I(R,z)$,

which states that the composite budget share equation written in terms of the group price indices, $G_I(R,z)$, is equal to the conditional expected value of the sum over the elementary budget share equations, $G_I^*(r,z)$, when the elementary prices are written as deviations from the group price indices, $R^* + \rho = r$. Lewbel (1996) uses equation (4) to obtain results that relate directly to demand system estimation. First, $G_I(R,z)(I = 1, \dots, N)$ is a valid system of composite demand equations because this system inherits the adding-up, homogeneity, and nearly (or in some cases exactly) inherits symmetry from the elementary demands. Second, the demand elasticities of $G_I(R,z)$ are best, unbiased estimates of within-group sums of elementary demand elasticities.

As for empirical testing, following Lewbel (1996) and Reed et al. (2005), we define p_i is the mean-deflated price index of good i and p_I is the mean-deflated Törnqvist price index I that contains good i. Let $\gamma_i = ln(p_i)$ and $R_I = ln(P_I)$ the i_{th} relative price can be presented as:

(6) $\rho_i = \gamma_i - R_I$.

According to Lewbel (1996), a valid aggregation requires that ρ_i is independent of R_I. Therefore, testing whether GCCT holds or not is equivalent to testing whether ρ_i and R_I are independent of each other. Following Lewbel (1996), tests depend on panel time series properties of the data. The procedure can be described as two steps: (1) determine the stationarity of each ρ_i and R_I using unit root tests; (2) based on the results of step 1, test the independences between ρ_i and R_I. Three possible results can be specified from the first step: if both ρ_i and R_I are stationary, a correlation test will be conducted to test independence; if ρ_i and R_I are both nonstationary, a cointegration test will be conducted to test independence; if ρ_i is stationary and R_I is nonstationary, or R_I is stationary and R_I is nonstationary, then no test is required because two series cannot be cointegrated when one is stationary and the other is not.

4.2 Quadratic Almost Ideal Demand Model

We choose the quadratic almost ideal demand (QUAID) (Banks et al. 1997) as the demand function. Compared with the almost ideal demand (AID), QUAID has more flexible Engel curves but retains the exact aggregation property of AID so that market-level data can be used to make inferences about consumer behavior. The conditional budget share equation within one meat group is:

(7) $w_{mit} = \alpha_{mit} + \sum_{j=1} \gamma_{ij} ln(p_{mjt}) + \beta_i ln\left[\frac{x_{mt}}{a(P_{mt})}\right] + \frac{\vartheta_i}{b(p_{mt})}\left\{\ln\left[\frac{x_{mt}}{a(p_{mt})}\right]\right\}^2 + e_t$

where w_{mit} is the expenditure share of meat category i in market m and time t, p_{mjt} is the price index of category j, n is the number of meat categories within group, x_{mt} is the total meat expenditure. The $a(P_{mt})$ and $b(p_{mt})$ terms are defined as

(8) $\ln a(P_{mt}) = \alpha_0 + \sum_{i=1}^{n} a_{i0} ln p_{mit} + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} p_{mit} * p_{mjt}$, and

(9) $b(p_{mt}) = \sum_{i=1}^{n} p_{mit}^{\beta_i}$.

We assume the intercept α_{mit} to be a linear function of market and seasonal fixed effects

(10) $\alpha_{mit} = \alpha_{i0} + \sum_{i=2}^{n} \alpha_{il} mkt_{ml} + \sum_{i=2}^{n} \alpha_{ir} sea_{tr}$

where mkt_{ml} and sea_{tr} are dummy variables for market l and the r_{th} time period within a specific year.

4.3 Log Translog Demand Model

To check sensitivity of our findings to functional form assumptions, we perform robustness checks by using the log TL version of the translog demand system by Pollak and Wales (1992). We choose the log TL model for two reasons. First, it has been used extensively in meat demand literature and provides a good statistical fit to the U.S. meat consumption data, even in comparison with members of the class of globally flexible models (Holt, Matthew T., and Barry K. Goodwin 2009). Second, log TL model reduces the number of free parameters in the Slutsky matrix, making it more feasible to check curvature conditions. The conditional log TL budget share equation within one meat group is:

(11) $w_{mit} = \frac{\alpha_{mit} + \sum_{j=1} \gamma_{ij} \ln(p_{mjt}/x_{mt})}{-1 + \sum_{j=1} c_j \ln(p_{mjt}/x_{mt})} + e_t$

where w_{mit} is the expenditure share of meat category i in market m and time t, p_{mjt} is the price index of category j, n is the number of meat categories within group, x_{mt} is the total meat expenditure. We assume the intercept α_{mit} to be a linear function of market and seasonal fixed effects

(12) $\alpha_{mit} = \alpha_{i0} + \sum_{i=2}^{n} \alpha_{il} mkt_{ml} + \sum_{i=2}^{n} \alpha_{ir} sea_{tr}$

where mkt_{ml} and sea_{tr} are dummy variables for market l and the r_{th} time within a specific year. Finally, compared with basic TL specification, the additional restriction:

(13) $\sum_{j=1} c_j = 0$

is imposed in estimation.

5. Empirical Result

This section presents tests for valid aggregation of 17 elementary meat products and estimates of composite meat demand elasticities. We have three categories of meat: beef, pork and chicken. Within beef, we have 7 products: ground, loin, round, rib, chuck, miscellaneous and variety ranked in descending order of market share. For pork, we have 5 products: loin, ribs, shoulder, miscellaneous and variety. For chicken, we have 5 products: breast, whole bird, leg, thighs, and wings.

5.1 GCCT test results

This section presents GCCT tests for valid aggregation of 17 elementary meat products. Tables 1 and 2 summarize the GCCT tests for aggregation based on both time series and panel data. In the time series setting, following Lewbel (1996), two stationary tests were conducted: ADF test with the null of nonstationarity and KPSS test with the null of stationarity. Having two tests introduces the possibility of conflicting results. Therefore, inferences based on the joint confirmation hypothesis (JCH) of a unit root were used when the ADF and KPSS tests conflicted (Carrion-i-Silvestre et al., 2001). In the panel setting, two panel-data unit-root tests were conducted: Harris–Tzavalis (1999) test and Fisher-type (Choi 2001) test, both assume nonstationary data under the null. Having two tests introduces the possibility of conflicting results. Inferences will be based on Levin–Lin–Chu test (2002).

First, a low statistical power GCCT test is implemented and this result is consistent with conventional grouping method (a single beef, pork and chicken composite). As indicated in table 1, for GCCT tests based on time series price indices, the group prices for all three meat products were nonstationary and 3(beef), 5(pork), and 3 (chicken) of the 20 relative elementary prices were nonstationary. Engle-Granger tests were used to test for cointegration. Since the Engle-Granger tests all failed to reject the null of a spurious regression for all of the individual price comparisons, there was no need to perform family-wise tests. The individual test results support the notion that we can obtain reliable information by using the data to form a single beef, pork and chicken composite. All meat subgroups can be aggregated based on this time series setting.

Next, a high statistical power approach is implemented and new results are obtained. In table 2, for *GCCT* tests based on panel price indices, the group price index for beef was nonstationary, indices for pork and chicken were stationary and all 20 relative prices were stationary; consequently, for pork and chicken, where relative prices were stationary, aggregation depends on correlation tests alone. Spearman's rank correlation tests were used to test for correlation. Since the Spearman's correlation tests all rejected the null of independence for all the individual price comparisons, the individual test results support the notion that we cannot obtain reliable information by aggregating pork and chicken products into a pork composite and a chicken composite. For beef, further testing is not needed because the group price index for beef was nonstationary and all relative prices were stationary. Two series cannot be cointegrated when one is stationary and the other is not. Therefore, all beef products can be aggregated into a beef composite for the purpose of estimating demand. In summary, these results suggest that we can obtain reliable information by forming a single beef composite but not by aggregating pork and chicken products into a pork and a chicken composite.

This panel *GCCT* result is further supported by results from the log TL demand estimation. The number of observations that satisfy the curvature requirements of negative semi-definiteness of the Slutsky matrix is much higher based on the tested groupings than that based on conventional groupings, which means aggregated pork and chicken fail to satisfy the theoretical regularity conditions compared with disaggregated pork and chicken products (described in section 6).

5.2 Quadratic Almost Ideal Demand System estimation on meat products

In this section, we present the estimates of the uncompensated own- and cross-price elasticities of the composite meat incomplete demand system based on the tested groupings and conventional groupings. Aggregation biases in elasticity estimation were also calculated.

5.2.1 Results without correcting price endogeneity

Quadweek data are employed in estimation, so there are substantial seasonal patterns for some of the variables, most notably for purchase quantities. To address seasonality, we introduced a set of market and time fixed effects in each model. Table 3 and Table 4 show results of price elasticities for both conventional groupings and tested groupings without correcting price endogeneity. In both tables, all own-price elasticities are negative and statistically significant at the 1% level.

Given that using tested groups gives us more precise and stable estimates of price elasticities, it is necessary to compute the discrepancy in estimated elasticities between the tested groups and conventional groups. This discrepancy is measured by "aggregation bias[1]" which is defined as the percentage change in price elasticities of conventional groups compared with those of tested groups. To make the price elasticities of two groups comparable, we simulated a scenario for tested groups that the price of each product of each meat category increases by 1%. Under this scenario, we calculate the percent change in the demand of each meat product, take the market-share-weighted average, and sum up by categories. We obtained the price elasticities of four categories like Table 3. Table 5 presents simulated estimates of the uncompensated own- and cross- price elasticities of the meat demand system based on tested

[1] The aggregation bias under inconsistent aggregation is defined as $= 100\% \times \frac{\varepsilon_c - \varepsilon_t}{\varepsilon_t}$, where ε_c represents own-/cross-price elasticities supported by conventional groupings, and ε_t represents the corresponding own-/cross-price elasticities based on the groupings suggested by the GCCT test results.

groupings.

Table 6 contains the aggregation biases of the uncompensated own- and cross-price elasticities of the incomplete demand system for composite meat under inconsistent aggregation. Compared with the simulated elasticities for tested groups as shown in Table 5, all the own-price elasticities are over-estimated. In addition, 8 of the 12 cross-price elasticities are over-estimated, 4 of them are under-estimated. Serious biases were found in cross-price elasticities of chicken and pork products (inconsistent aggregation products) that the absolute aggregation biases are all over 200%, and that the estimated cross-price elasticity of pork with respect to chicken even has a reverse sign. The response of the quantity demanded for pork to the price change of chicken is wrongly evaluated due to inconsistent aggregation.

5.2.2 Results with correction for price endogeneity

Apparently, it is not reasonable to assume strict price exogeneity in demand estimation. To address this problem, we adopted distance-weighted instruments in the demand model. We calculated Euclidian distances from the centroid of each market to the centroids of all other markets within 300 miles. The instrument for each product-level market price index was calculated as the weighted average of the price indices of the same meat product for all other markets. The inverse of the Euclidian distances between the target market and other markets were used as the weight. Table 7 and Table 8 show results of price elasticities for both conventional groupings and tested groupings with correcting price endogeneity. In both tables, all own-price elasticities are negative and statistically significant at 1% level.

A similar scenario discussed in Section 5.2.1 is simulated for the tested groups that the price of each product of each meat category increases by 1%. Table 9 presents simulated estimates of the uncompensated own- and cross- price elasticities of the meat demand system for tested groupings. Table 10 contains the aggregation biases of the uncompensated own- and cross-price elasticities of the incomplete demand system for composite meat under inconsistent aggregation. Compared with the simulated elasticities for tested groups as shown in Table 7, own-price elasticities of beef and pork are over-estimated, and chicken's own-price elasticity is underestimated. In addition, 5 of the 12 cross-price elasticities are over-estimated, 5 of them are under-estimated, and 2 of them yield the same value as in Table 7. All the elasticity estimates have the same sign as elasticities from consistent aggregation. We observed that the maximum aggregation bias is 27% excluding *numéraire*, so we conclude that no serious aggregation biases were found. Being motivated by the results shown in Table 6 and Table 10, we propose that after accounting for endogenous prices in an incomplete meat demand model, the aggregation bias from the wrong aggregation could be numerically reduced significantly (more described in section 5.2.3).

5.2.3 A comparison of results of inproper aggregation based on different assumptions

To support our assumption that aggregation bias due to the wrong aggregation could be numerically reduced by using instrumental variables (IVs), we calculated the mean and weighted relative estimation biases and compared these two statistics under strict price exogeneity assumption and price endogeneity assumption. Table 11 presents the numbers of over-estimated, under-estimated, exact-estimated elasticities and elasticity estimations with reverse signs under each assumption. Mean relative and sales-weighted relative aggregation biases[2] are also included in the table. We find that magnitude of own-/cross- price elasticities have a systematic tendency to be over-estimated if we assume prices are exogenous. In addition, aggregation biases in cross-price elasticities are greatly reduced when using IVs. The mean relative and weighted relative aggregation biases are reduced from 144.6% to 11.7% and from 427.3% to 26%, respectively. 91.91% and 93.92% of the aggregation biases are corrected by using distance-weighted instrumental variables. We find that the aggregation biases in demand study are largely embedded in the endogeneity problem. If price endogeneity is controlled, the aggregation errors will be largely decreased.

6. Robustness Check

We conducted a robustness check by estimating Log Translog (Log TL) demand system to determine whether the demand model specification biased our results. First, Table 12, similar to Table 11, displays mean relative and weighted relative aggregation biases based on Log TL demand system. The mean relative and weighted relative aggregation biases are considerably large if no *IVs* are implemented, especially for cross-price elasticities. Like the results in QUAID, the mean relative and weighted aggregation biases in cross-price elasticities reduced from 436.3% to 56.4% and from 1429.7% to 144.8%, respectively. Thus 87.07% and 89.87% of the aggregation biases are corrected by using *IVs*. In addition, the improvements in the estimation of own-price elasticities are much higher by using Log TL than those yielded by QUAID. Moreover, with the control for price endogeneity, we obtained a rather small mean relative and sales-weighted relative aggregation biases of 1.5% and 1.6%, respectively, indicating the discrepancy in the elasticities based on conventional groups and tested groups are minimal.

Second, the panel GCCT test result is further supported by the curvature conditions of the log TL demand estimation. One issue that arises frequently in the estimation of demand systems is the imposition of curvature (negativity) conditions (Barten and Geyskens 1975). Quasi–concavity of the utility function implies that the Slutsky matrix will be negative semi–definite. Based on our demand estimation, only 15 (0.42%) of the observations violate the curvature requirements of negative semi-definiteness of the Slutsky matrix for tested groups, while 118 (3.31%) of the observations violate the curvature requirements for conventional groups. It means that the model supported by panel GCCT is more consistent with economic theory and gives a better fit for the actual consumption behavior. Moreover, these violations of regularity invalidate the maintained hypothesis and the duality theory that are

[2] The relative aggregation bias under inconsistent aggregation is defined as $= 100\% \times \left|\frac{\varepsilon_c - \varepsilon_t}{\varepsilon_t}\right|$, where ε_c represents own-/cross-price elasticities supported by conventional groupings, and ε_t represents the corresponding own-/cross-price elasticities based on the groupings suggested by the GCCT test results.

incorporated in the estimated demand model. Therefore, the result of the panel GCCT test that a single pork composite or a chicken composite cannot be constructed is further supported.

7. Conclusion

In this paper, we report tests of aggregation over elementary beef, pork, and chicken products, and revisit the demand for meat products in the United States. Unlike the standard time series-based unit-root and cointegration tests used in the literature, we apply a panel GCCT test that better distinguishes highly persistent stationary processes from nonstationary processes. The reason for this is that panel data better controls the size and power problems existed in time-series test schemes. The empirical results indicate that we can obtain reliable demand information by forming a beef composite, but not by combining pork and chicken products into a pork composite and a chicken composite. In addition, in terms of compliance with consumer rationality, we have shown that tested groupings (aggregated beef, disaggregated pork and chicken) comply with more of the curvature assumption embedded in Log TL demand system than the traditional groupings (aggregated beef, pork, and chicken) do.

Another objective of this paper, however, has been to suggest a possible solution to the inconsistent aggregation problem. The solution lies in employing instrumental variables to control for price endogeneity caused by improper aggregation. By estimating the demand model separately based on the conventional groupings and groupings suggested by tests, we find that the magnitude of the errors in estimated cross-price elasticities of pork and chicken (which cannot be aggregated) is large. However, after correcting for price endogeneity by instrumental variables, the degree of aggregation bias is significantly reduced. For QUAID, 91.91% and 93.92% of the aggregation biases in cross elasticities are corrected by using instruments. For the log TL model, 87.07% and 89.87% of the aggregation biases in cross elasticities are corrected and 82.53% and 84.39% of aggregation biases in own price elasticities are corrected by using instruments.

In applied demand analysis, the researcher is often compelled to aggregate elementary products to a higher level of aggregation prior to econometric estimation. In many cases, the aggregation scheme is ad hoc and, at best, based on intuition. However, when the untested aggregation scheme is not appropriate, the degree of bias in the elasticity estimates may be significant as demonstrated in the case of U.S. meat demand. We have shown that the use of instrumental variables may be able to substantially mitigate the degree of bias in lieu of explicit testing of aggregation schemes. Because instrumental variable approaches are already advocated for demand studies for other reasons (Zhen et al. 2014), this finding is good news for practitioners of demand system estimation.

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Table 1 Generalized Composite Commodity Theorem test results based on time series data

Group and relative prices	Aggregate share (%)	ADF Test H0:*I(1)* [a]	KPSS Test H0:*I(0)* [b]	*I(1)* or *I(0)* [c]	Engle-Granger Test Ho: Not Cointegrated (NC)[d]	Aggregation or Not (Y/N)
		τ_t	η_t		T_k	
R(Beef)	90.5656	-1.322(5)	0.4973(2)**	I(1)		Y
ρ_{ground}	29.6625	-3.511(7)**	0.0789(2)	I(0)	NC	Y
ρ_{loin}	21.8298	-3.812(5)**	0..0715(2)	I(0)	NC	Y
ρ_{round}	11.7779	-3.516(3)*	0.1793(2)**	I(0)	NC	Y
ρ_{rib}	10.8272	-1.886(10)	0.2088(2)**	I(1)	-3.861	Y
ρ_{chuck}	8.9069	-4.456(1)**	0.1548(2)**	I(0) (JCH)	NC	Y
ρ_{misc}	6.2441	-4.897(0)**	0.072(2)	I(0)	NC	Y
$\rho_{variety}$	1.3172	-2.355(0)	0.1973(2)**	I(1)	-1.916	Y
R(Pork)	98.1385	-2.267(5)	0.2678(2)**	I(1)		Y
ρ_{loin}	59.1	-4.920(0)**	0.2638(2)**	I(0) (JCH)	NC	Y
ρ_{ribs}	24.7765	-5.440(5)**	0.0555(2)	I(0)	NC	Y
$\rho_{shoulder}$	9.9581	-2.621(2)	0.2408(2)**	I(1)	-4.698	Y
ρ_{misc}	3.2573	-2.398(5)	0.2179(2)**	I(1)	-1.669	Y
$\rho_{variety}$	1.0466	-1.886(1)	0.3159(2)**	I(1)	-1.561	Y
R(chicken)	92.4182	-1.288(5)	0.5124(2)**	I(1)		Y
ρ_{breast}	56.0849	-2.469(5)	0.1025(2)	I(1) (JCH)	-1.22	Y
$\rho_{wholebir}$	12.385	-2.405(5)	0.1390(2)*	I(1)	-1.154	Y
ρ_{leg}	8.8262	-3.705(8)**	0.3472(2)**	I(0) (JCH)	NC	Y
ρ_{thighs}	8.3751	-2.424(2)	0.0808(2)	I(1) (JCH)	-1.24	Y
ρ_{wings}	6.747	-2.562(6)	0.3897(2)**	I(1)	-1.022	Y
10% critical value		-3.172	0.119	(-3.671,0.073)	-5.5	

Asterisk (*) denotes rejection of the null at the 0.10 significance level, and (**) denotes rejection of the null at the 0.05 significance level.

[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) t-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by Stata 14.0.

[b] The test statistics (η_t) of the null hypothesis of I(0) are the Kwaitkowski et al. (1992) (KPSS) t-statistics. The t-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. For the correction of the error term, a Bartlett window with five lags was used to ensure the variance matrix was well behaved.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Carrion-i-Silvestre et al., 2001). The joint critical values of (–3.671, 0.073) represent the critical values for fifty and hundred observations for the ADF and the KPSS with the trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than –3.671 and the value of the KPSS statistic is less (greater) than 0.073 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

[d] The test statistics (T_k) of the null hypothesis is that the kth relative price and the vector of composite group prices are not cointegrated are augmented Dickey-Fuller tests of *I(1)* residuals from regressing the kth relative price on each of the integrated group price indices. The 0.10 critical values reported for the individual tests are based on 65 observations.

Table 2 Generalized Composite Commodity Theorem test results based on panel data

Group and relative prices	Aggregate share (%)	HZ Test: H0: $I(1)$ [a]	Fisher-Type Test: H0: $I(1)$ [b]	$I(1)$ or $I(0)$ [c]	Spearman Test[d]: H_0: Independent	Aggregation or Not (Y/N)
		η_t	z_t		ρ	
R(Beef)	90.5656	-1.0732	0.4304(4)	I(1)		Y
ρ_{ground}	29.6625	-45.9185**	-26.2017(4)**	I(0)	N/A	Y
ρ_{loin}	21.8298	-43.3458**	-26.1851(4)**	I(0)	N/A	Y
ρ_{round}	11.7779	-74.7619**	-39.8026(4)**	I(0)	N/A	Y
ρ_{rib}	10.8272	-79.5057**	-42.9098(4)**	I(0)	N/A	Y
ρ_{chuck}	8.9069	-80.1352**	-42.2686(4)**	I(0)	N/A	Y
ρ_{misc}	6.2441	-80.1352**	-27.8820(4)**	I(0)	N/A	Y
$\rho_{variety}$	1.3172	-41.1671**	-12.3297(4)**	I(0)	N/A	Y
R(Pork)	98.1385	-17.4228**	-10.34(4)**	I(0)		N
ρ_{loin}	59.1	-65.3571**	-35.5773(4)**	I(0)	0.2734**	N
ρ_{ribs}	24.7765	-63.6428**	-33.0278(4)**	I(0)	-0.0320**	N
$\rho_{shoulder}$	9.9581	-42.6096**	-25.4329(4)**	I(0)	-0.4474**	N
ρ_{misc}	3.2573	-31.8951**	-19.39(4)**	I(0)	0.3623**	N
$\rho_{variety}$	1.0466	-12.7714**	-9.5719(4)**	I(0)	0.1419**	N
R(chicken)	92.4182	-18.0477**	-13.5848(4)**	I(0)		N
ρ_{breast}	56.0849	-61.8058**	-34.5630(4)**	I(0)	-0.3716**	N
$\rho_{wholebir}$	12.385	-57.8510**	-36.8508(4)**	I(0)	0.0877**	N
ρ_{leg}	8.8262	-55.6498**	-31.5335(4)**	I(0)	0.3014**	N
ρ_{thighs}	8.3751	-62.9381**	-36.1654(4)**	I(0)	0.1959**	N
ρ_{wings}	6.747	-32.8861**	-24.5561(4)**	I(0)	0.3940**	N

Asterisk (*) denotes rejection of the null at the 0.10 significance level, and (**) denotes rejection of the null at the 0.05 significance level.

[a] The test statistics (η_t) of the null hypothesis of $I(1)$ are the (1999) Harris and Tzavalis t-tests with fixed effects and time effects in the fitted equation.

[b] The inverse normal test statistics (z_t) of the null hypothesis of $I(1)$ Fisher-type (Choi 2001) tests that conduct Phillips-Perron unit-root tests on each panel. The null hypothesis means that there are no unit roots in the panels under the given test conditions (included panel mean and time trend).

[c] Having all of the two tests introduces the same testing results, there is no need to do additional unit-root tests based on this panel.

[d] The ρ represents Spearman's rank correlation coefficient, and the significance is determined by the observed correlation and the sample size of the panel dataset.

Table 3. Median Uncompensated Price Elasticities for conventional groupings without correcting price endogeneity.

Elasticity of the quantity of	With respect to the price of 1.Beef	2.Pork	3.Chicken	4. Numeraire
1.Beef	**-0.832**	-0.076	0.175	0.544
	-215.735	-30.177	101.467	87.448
2.Pork	-0.255	**-0.648**	-0.132	1.075
	-30.133	-59.832	-20.735	54.596
3.Chicken	0.439	-0.099	**-1.683**	1.357
	101.647	-20.723	-360.283	128.470
4. Numeraire	-0.001	0.000	0.000	**-1.003**
	-51.013	2.145	44.578	-37745.549

Notes: All elasticities and their t-values are median values over IRI markets. Boldface numbers are own-price elasticities. Results are based on the incomplete demand model that does not account for price endogeneity.

Table 4. Median Uncompensated Price Elasticities for tested groupings without correcting price endogeneity.

Elasticity of the quantity of		With respect to the price of											
		Beef	Pork					Chicken					Numeraire
		1. Beef	2. Loin	3. Ribs	4. Shoulder	5. Misc	6. Variety	7.Breast	8.Wholebir	9. Leg	10. Thighs	11. Wings	12. Numeraire
Beef	1.Beef	**-0.823**	-0.047	-0.012	-0.013	0.029	-0.015	0.038	-0.093	-0.008	0.031	0.076	0.650
		-237.515	-22.963	-12.359	-20.718	82.560	-42.801	36.493	-151.241	-27.985	83.154	152.221	108.307
Pork	2. Loin	-0.254	**-1.470**	0.585	0.109	0.009	-0.020	-0.138	0.081	-0.016	-0.049	-0.080	1.194
		-22.948	-185.468	120.098	40.942	5.606	-13.805	-33.804	31.241	-13.821	-26.873	-33.786	67.542
	3. Ribs	-0.165	1.553	**-2.514**	0.442	0.124	0.038	-0.086	-0.091	0.027	-0.053	-0.108	0.876
		-12.337	120.097	-231.369	100.826	48.873	13.134	-12.937	-18.612	10.119	-14.953	-27.566	38.481
	4. Shoulder	-0.460	0.719	1.101	**-1.873**	-0.076	0.265	0.520	0.023	-0.042	0.182	-0.282	0.214
		-20.691	40.947	100.825	-236.446	-16.942	53.348	59.615	5.069	-10.178	34.512	-44.032	6.106
	5. Misc	3.860	0.229	1.142	-0.281	**-1.967**	-0.096	1.465	0.102	0.210	0.088	-0.017	-4.177
		82.603	5.611	48.875	-16.941	-101.870	-7.741	58.012	5.776	15.099	5.943	-2.680	-52.231
	6. Variety	-6.814	-1.663	1.201	3.368	-0.330	**-3.197**	7.999	-0.644	0.812	2.933	0.079	-1.022
		-42.777	-13.800	13.137	53.350	-7.741	-59.128	108.336	-8.181	22.259	61.879	0.660	-7.190
Chicken	7.Breast	0.172	-0.116	-0.027	0.066	0.050	0.080	**-1.792**	0.015	-0.025	0.029	0.088	1.472
		36.604	-33.786	-12.931	59.618	58.009	108.332	-544.634	7.941	-34.876	32.324	68.560	148.733
	8.Wholebir	-1.911	0.307	-0.129	0.013	0.016	-0.029	0.068	**-2.083**	0.253	0.122	0.145	3.272
		-151.200	31.240	-18.610	5.066	5.774	-8.184	7.935	-327.256	94.890	36.851	31.345	142.606
	9. Leg	-0.219	-0.084	0.055	-0.034	0.046	0.052	-0.158	0.357	**-1.622**	-0.143	-0.005	1.984
		-27.882	-13.800	10.126	-10.177	15.098	22.257	-34.866	94.900	-380.469	-42.192	-0.924	148.353
	10. Thighs	0.954	-0.277	-0.113	0.156	0.020	0.198	0.199	0.184	-0.153	**-1.158**	0.089	0.033
		83.226	-26.865	-14.949	34.512	5.943	61.876	32.328	36.855	-42.192	-186.118	18.487	1.506
	11. Wings	3.132	-0.606	-0.311	-0.325	-0.005	0.007	0.804	0.293	-0.008	0.119	**-1.098**	-1.499
		152.287	-33.782	-27.563	-44.032	-2.680	0.659	68.562	31.348	-0.923	18.488	-111.477	-46.566
Numeraire	12. Numeraire	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**-1.003**
		-34.594	18.136	-6.230	-34.617	-85.129	-24.357	54.095	113.125	65.717	-64.498	-98.997	-39638.989

Notes: All elasticities and their t-values are median values over IRI markets. Boldface numbers are own-price elasticities. Results are based on the incomplete demand model that does not account for price endogeneity.

Table 5. Simulated Median Uncompensated Price Elasticities for tested groupings without correcting price endogeneity.

Elasticity of the quantity of	With respect to the price of			
	1.Beef	2.Pork	3.Chicken	4. Numeraire
1.Beef	**-0.823**	-0.057	0.044	0.650
2.Pork	-0.186	**-0.589**	0.021	0.812
3.Chicken	0.142	-0.033	**-1.440**	1.415
4. Numeraire	0.000	0.000	0.000	**-1.003**

Table 6. Aggregation biases for conventional groupings without correcting price endogeneity.

	1.Beef	2.Pork	3.Chicken	4. Numeraire
1.Beef	**1%**	33%	296%	-16%
2.Pork	37%	**10%**	-718%	32%
3.Chicken	208%	200%	**17%**	-4%
4. Numeraire	63%	-121%	7%	**0%**

Notes: The positive number means that the own-/cross- elasticity is overestimated by conventional groupings, and the negative number means that the own-/cross- elasticity is underestimated by conventional groupings.

Table 7. Median Uncompensated Price Elasticities for conventional groupings after correcting price endogeneity.

Elasticity of the quantity of	With respect to the price of 1.Beef	2.Pork	3.Chicken	4. Numeraire
1.Beef	**-0.900**	-0.181	0.155	-1.372
	-11.626	-3.036	7.540	-6.948
2.Pork	-0.609	**-0.944**	-0.945	-2.284
	-3.037	-2.401	-9.355	-1.583
3.Chicken	0.387	-0.710	**-1.106**	-1.712
	7.507	-9.374	-28.246	-10.050
4. Numeraire	0.000	0.001	0.000	**-0.994**
	-1.074	2.762	4.368	-909.046

Notes: All elasticities and their t-values are median values over IRI markets. Boldface numbers are own-price elasticities. Results are based on the incomplete demand model that assuming price endogeneity.

Table 8. Median Uncompensated Price Elasticities for tested groupings after correcting price endogeneity.

Elasticity of the quantity of		With respect to the price of											
		Beef	Pork					Chicken					Numeraire
		1. Beef	2. Loin	3. Ribs	4. Shoulder	5. Misc	6. Variety	7.Breast	8.Wholebir	9. Leg	10. Thighs	11. Wings	12. Numeraire
Beef	1.Beef	**-0.837**	-0.089	-0.039	-0.038	-0.007	-0.002	0.064	0.009	0.024	0.016	0.008	-1.378
		-9.713	-0.797	-1.529	-2.318	-1.251	-0.259	1.520	0.480	3.714	1.755	1.389	-4.070
Pork	2. Loin	-0.483	**-1.221**	0.077	0.182	0.065	-0.001	-0.544	0.015	-0.107	-0.053	-0.114	-1.694
		-0.806	-2.931	0.652	3.539	3.283	-0.868	-4.727	0.056	-4.795	-1.663	-2.708	-1.420
	3. Ribs	-0.571	0.202	**-2.025**	0.406	0.018	0.000	-0.563	-0.254	-0.069	-0.224	-0.281	-4.109
		-1.552	0.650	-6.745	3.458	0.286	-0.016	-3.006	-1.740	-1.779	-3.615	-7.629	-2.122
	4. Shoulder	-1.354	1.206	1.012	**-2.294**	0.037	0.072	-0.515	0.021	-0.032	-0.096	-0.030	-2.486
		-2.323	3.539	3.460	-20.409	0.326	0.814	-2.664	-0.233	-0.384	-1.082	-0.410	-1.446
	5. Misc	-0.901	1.590	0.168	0.138	**-1.213**	-0.348	-1.677	-0.111	-0.075	-0.492	-0.406	0.186
		-1.249	3.283	0.287	0.326	-4.528	-2.119	-6.736	-0.755	-0.049	-2.500	-2.548	-0.290
	6. Variety	-1.105	-0.122	-0.011	0.913	-1.194	**-0.754**	-0.904	-0.475	-2.974	2.120	-0.258	0.926
		-0.263	-0.868	-0.016	0.814	-2.119	-1.009	-0.999	-1.249	-7.803	3.847	-1.682	-0.416
Chicken	7.Breast	0.285	-0.455	-0.177	-0.065	-0.057	-0.009	**-1.265**	0.060	-0.018	0.038	-0.025	-1.686
		1.506	-4.739	-2.995	-2.657	-6.729	-0.996	-24.599	3.843	-1.264	3.150	-1.394	-4.672
	8.Wholebir	0.174	0.057	-0.361	0.012	-0.017	-0.021	0.272	**-2.391**	0.329	0.185	0.221	-0.566
		0.485	0.061	-1.737	-0.231	-0.755	-1.249	3.851	-17.681	7.209	5.367	4.103	-0.904
	9. Leg	0.694	-0.574	-0.138	-0.026	-0.016	-0.189	-0.115	0.464	**-1.950**	0.166	-0.040	-1.981
		3.694	-4.796	-1.771	-0.383	-0.049	-7.805	-1.262	7.208	-22.905	3.632	-0.504	-6.311
	10. Thighs	0.501	-0.302	-0.480	-0.083	-0.114	0.143	0.256	0.278	0.177	**-1.591**	0.130	-2.155
		1.745	-1.662	-3.609	-1.080	-2.500	3.848	3.157	5.364	3.633	-17.516	2.093	-4.323
	11. Wings	0.345	-0.865	-0.806	-0.034	-0.126	-0.023	-0.230	0.444	-0.056	0.174	**-1.066**	-1.159
		1.382	-2.704	-7.631	-0.409	-2.547	-1.682	-1.393	4.102	-0.504	2.093	-7.325	-1.351
Numeraire	12. Numeraire	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**-0.995**
		-0.460	1.645	2.942	0.806	2.589	2.084	2.872	2.325	1.737	0.104	3.292	-684.569

Notes: All elasticities and their t-values are median values over IRI markets. Boldface numbers are own-price elasticities. Results are based on the incomplete demand model that assuming price endogeneity.

Table 9. Simulated Median Uncompensated Price Elasticities for tested groupings after correcting price endogeneity.

Elasticity of the quantity of	With respect to the price of 1.Beef	2.Pork	3.Chicken	4. Numeraire
1.Beef	**-0.837**	-0.175	0.121	-1.378
2.Pork	-0.614	**-0.892**	-1.020	-2.294
3.Chicken	0.333	-0.808	**-1.183**	-1.568
4. Numeraire	0.000	0.001	0.000	**-0.995**

Table 10. Aggregation Biases under inconsistent aggregation for tested groupings after correcting price endogeneity.

	1.Beef	2.Pork	3.Chicken	4. Numeraire
1.Beef	**7%**	3%	27%	0%
2.Pork	-1%	**6%**	-7%	0%
3.Chicken	16%	-12%	**-6%**	9%
4. Numeraire	-33%	3%	-28%	**0%**

Notes: The positive number means that the own-/cross- elasticity is overestimated by conventional groupings, and the negative number means that the own-/cross- elasticity is underestimated by conventional groupings.

Table 11. Comparison of under the price exogeneity assumption and price endogeneity assumption.

	Price Exogeneity Assumption	Price Endogeneity Assumption	Improvements in aggregation biases[a]
Own-Price Elasticities			
Over-estimated	3	2	
Under-estimated	0	1	
Exact-estimated	1	1	
Mean relative estimation errors	7.0%	5.0%	29.05%
Sales-Weighted relative estimation errors (except the *numéraire* good)	6.5%	6.9%	-6.93%
Cross-Price Elasticities			
Over-estimated	8	5	
Under-estimated	4	5	
Exact-estimated	0	2	
Reverse Sign	1	0	
Mean relative estimation errors	144.6%	11.7%	91.91%
Sales-Weighted relative estimation errors (except the *numéraire* good)	427.3%	26.0%	93.92%

[a] The improvements in aggregation biases are calculated as $\tau = 100\% \times (\epsilon_i - \epsilon_n)$. Where ϵ_i represents mean relative/sales-weighted relative aggregation biases under the price exogeneity assumption, and ϵ_n represents the corresponding mean relative/sales-weighted relative aggregation biases under the price endogeneity assumption. The positive number means the percentage of decrease in aggregation biases when using instrumental variables to control price endogeneity.

Table 12. Comparison of aggregation biases under the price exogeneity assumption and price endogeneity assumption based on Log Translog Demand.

	Price Exogeneity Assumption	Price Endogeneity Assumption	Improvements in aggregation biases[a]
Own-Price Elasticities			
Over-estimated	1	2	
Under-estimated	2	1	
Exact-estimated	1	1	
Mean relative estimation errors	8.6%	1.5%	82.53%
Sales-Weighted relative estimation errors (except the *numéraire* good)	10.2%	1.6%	84.39%
Cross-Price Elasticities			
Over-estimated	4	5	
Under-estimated	3	5	
Exact-estimated	0	2	
Reverse Sign	5	0	
Mean relative estimation errors	436.3%	56.4%	87.07%
Sales-Weighted relative estimation errors (except the *numéraire* good)	1429.7%	144.8%	89.87%

[a] The improvements in aggregation biases are calculated as $\tau = 100\% \times (\epsilon_i - \epsilon_n)$. Where ϵ_i represents mean relative/sales-weighted relative aggregation biases under the price exogeneity assumption, and ϵ_n represents the corresponding mean relative /sales-weighted relative aggregation biases under the price endogeneity assumption. The positive number means the percentage of decrease in aggregation biases when using instrumental variables to control for price endogeneity.