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Estimating Market Power Exertion in the U.S. Beef Packing Industry: An Illustration of Data Aggregation Bias Using Simulated Data

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Abstract: This study investigates data aggregation bias in estimating market power in the U.S. beef packing industry using New Empirical Industrial Organization (NEIO) models and shows empirical procedures that can alleviate the bias. Unlike many earlier studies in estimating market power exertion, our study examines the data aggregation bias when market-level data are used in place of firm-level data and show how the bias could be reduced. We first derive data aggregation bias analytically, then empirically investigate the aggregation bias by estimating both firm and aggregate industry models. Because the firm-level data are not available, we use simulated data generated from the Monte Carlo simulation method. Hybrid models, combining limited firm-level data with aggregate data, are also estimated to illustrate how the aggregation bias could be reduced. Our results show that aggregate models with industry-level data tend to underestimate market power exertion in the U.S. beef packing industry, and the aggregation bias is statistically significant at the 1% level. Comparing results from hybrid models with firm-level estimates, we find that hybrid models reduce the bias but do not remove the aggregation bias significantly. The sensitivity analysis shows that market power estimate and aggregation bias are sensitive to functional forms.

Keywords: data aggregation bias; conjectural elasticity; market power; new empirical industrial organization; beef packing industry; data simulation

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1. Introduction

The structure of the U.S. beef packing industry has continuously changed in recent years, mostly due to horizontal mergers. As a result, the concentration ratio from the four largest beef packers (CR4) has exceeded 80% since the early 1990s. The CR4 increased rapidly from below 40% in 1980 to over 80% in the early 1990s, then to 85% in 2020 [1]. Many studies in the industrial organization literature indicate that higher industry concentration leads to greater levels of market power exertion and market inefficiency (e.g., [2–9]). For example, Lopez et al. [3] estimate the oligopoly market power of 32 U.S. food processing industries and find a significant market power effect in many industries. Chung and Tostão [2] and Tostão et al. [5] examine packers' oligopsony power and find packers' market power exertion in the cattle procurement market. Recently, Bolotova [6] and López and Seoane [7] found that the recent COVID-19 outbreak further exacerbated packers' market power problem in the U.S. beef industry. However, many other studies also find that the market power effect is small or statistically insignificant (e.g., [10–12]).

Firms' anticompetitive behaviors could also affect sustainability. When firms take sustainability as a burden (e.g., additional environmental cost to address land degradation and carbon emission) against their profit maximization, market power exertion followed by high concentration should have a negative impact on sustainability. However, if large firms use sustainability for developing a business strategy to increase profit (e.g., Schumpeterian innovation), the high firm concentration could lead to a positive impact on sustainability, even though large firms exercise market power [13–18].

In the industrial organization literature, the Structure–Conduct–Performance (SCP) model was the dominant framework to estimate firms' market power exertion until the 1970s. However, limitations of the SCP model include the weak statistical relationship between structure (market concentration) and performance (profitability) due to the lack of firm-level profit data and the endogeneity of structure. The New Empirical Industrial Organization (NEIO) model, which emerged in the 1980s, has been developed mostly in reaction to the limitations of the SCP model. The new model estimates the firm's marginal cost function using market-level input cost data to derive an unobserved individual firm's profit, i.e., its price–cost margin. To address the endogeneity of the structure variable, the approach specifies a structural model with multiple behavioral equations. Therefore, the NEIO model is the preferred and most frequently used procedure to conduct market power analysis in the literature.

A large number of studies have applied the NEIO model to estimate the degree of market power in the U.S. beef packing industry, and many of these studies use industry-level data due to the lack of firm-level data, with only a few exceptions [2,4,5,11,19–21] (see also Table 1 for more examples). Chung and Tostão [2] estimate U.S. beef packers' market power using transaction data, and Driscoll, et al. [20] and Morrison Paul [4] estimate packers' market power using packing plant-level data. However, it is well known in empirical econometrics that when relations are derived at the individual level but are estimated using aggregated data, the data aggregation leads to biased parameter estimates. Therefore, packers' market power estimated using aggregate industry data without considering firm/plant heterogeneity is likely to be biased and inaccurate.

Table 1. A Survey of Market Power Estimation Studies for the U.S. Beef Packing Industry.

Study	Data Aggregation	Data Period	Market	Packing Industry	Evidence of Market Power
Lopez, et al. [3]	Annual	1972–1992	National	Beef and pork	Y
Morrison Paul [4]	Monthly	1992–1993	Plant	Beef	N
Schroeter [10]	Annual	1951–1983	National	Beef	Y
Schroeter, et al. [11]	Monthly	1990–1994	National	Beef	N
Crespi and Sexton [19]	Transaction data	1995–1996	Regional	Beef	Y
Driscoll, et al. [20]	Weekly	1992–1993	Plant	Beef	N
Azzam and Park [22]	Annual	1960–1977 1982–1987	National	Beef	Y
Azzam [23]	Monthly	1988–1991	National	Beef	Y
Azzam and Pagoulatos [24]	Annual	1959–1982	National	Beef and pork	Y
Chung, et al. [25]	Monthly	1980–2009	National	Beef	Y
Koontz, et al. [26]	Daily	1980–1982 1984–1986	Regional (State)	Beef	Y
Schroeter and Azzam [27]	Quarterly	1976–1986	National	Beef and pork	Y
Stiegert, et al. [28]	Quarterly	1972–1986	National	Beef	Y
Muth and Wohlgenant [29]	Annual	1967–1993	National	Beef	N

Source: [21,30].

Although aggregation bias is widely discussed in the econometrics literature, limited work to date has explicitly evaluated aggregation bias, particularly in estimating market power. The objective of this study is to investigate data aggregation bias in estimating market power for the U.S. beef packing industry using NEIO models and demonstrate whether one can alleviate the bias using a few of the empirical procedures proposed in the literature. We estimate market power from firm- and industry-level models and compare the estimates to examine the aggregation bias. Our study uses simulated data generated from the Monte Carlo simulation method because firm-level data are typically not available.

The Monte Carlo procedure produces individual firm data for 1000 firms for each month of 30 years' data, and the individual firm data are aggregated monthly for industry data. The Monte Carlo simulation procedure is further discussed in the data section in detail. Hybrid models, combining limited firm-level data with aggregate data, are also estimated to show if the aggregation bias can be reduced. A few studies in the consumer demand analysis propose ways to reduce the bias, but as far as we know, no previous studies have attempted to address this issue in NEIO models estimating market power exertion.

Our results find that data aggregation results in biased estimates and aggregate models estimated with industry-level data tend to underestimate market power exertion in the U.S. beef packing industry. Comparing results from firm-level models with hybrid models, we find that hybrid models reduce the bias but do not remove aggregation bias significantly. The sensitivity analysis shows that market power estimates and aggregation bias are sensitive to functional forms.

The next section presents a literature review of previous studies with a discussion of NEIO models and aggregation bias particularly focusing on the U.S. beef packing industry. We then provide detailed discussions on the data aggregation problem in econometric estimations of market power parameters, procedures to reduce the data aggregation problem, the data generation process, and results from our empirical models: firm-level, aggregate, and hybrid models. Finally, the last section presents a brief summary of findings and implications from our empirical analyses and directions for future studies.

2. Literature Review

Numerous studies have estimated market power exertion in agricultural and food industries; Table 1 provides a brief summary of selected studies estimating market power for the U.S. meat packing industry with a concentration on the beef industry. In Table 1, most studies use aggregate data, except two studies, those of Morrison Paul [4] and Driscoll, et al. [20], and out of fourteen studies, ten studies find evidence of market power exertion [3,10,19,22–28].

For example, Azzam and Pagoulatos [24], Schroeter and Azzam [27], and Azzam [23] estimate oligopoly and oligopsony market power in the U.S. meat packing industry and find that the level of oligopsony power from input market is higher than oligopolistic power from output market. Koontz, et al. [26], Stiegert, et al. [28], and Crespi and Sexton [19] use regional or national data for their estimations, but all three studies find packers' market power exertion in the cattle procurement market. Stiegert, et al. [28] attribute the low cattle price in the procurement market to packers' exercising of market power but also show that the low cattle price is influenced by cattle supply. Crespi and Sexton [19] suggest that the cattle procurement price is formed at about 5 to 10% lower than the competitive price due to packers' market power exertion. Schroeter [10] estimates packers' conjectural variation elasticity for 33 years between 1951 and 1983 and finds it statistically significant at the 1% level for 20 years and at the 5% level for 28 years, indicating market power exercise for most years. Based on the time-varying estimates of the market power parameter, he also concludes that packers' anticompetitive behavior did not increase under the increased packer concentration in the U.S. beef packing industry during the study period. Lopez, et al. [3] investigate the tradeoff relationship between oligopoly power and cost efficiency effects and show that the market power effect is higher than the cost efficiency effect in the meat packing industry.

However, a few studies in Table 1 find no evidence to support the existence of market power [4,10,11,20,29]. Schroeter, et al. [11] investigate market power from beef-packers and -retailers in the bilateral oligopoly setting. The study tests three market power hypotheses: bilateral (both packer and retailer) price-taking, packer price-taking, and retailer price-taking, and it finds that packer price-taking (i.e., no market power from packers) is the most consistent with the data. Muth and Wohlgenant [29] estimate the degree of oligopsony power in the beef procurement market and find that the market power parameter is not statistically significant. The authors suggest that the statistical insignificance of the market power estimate may be due to the use of aggregate national data because the national data do not reflect packers' anticompetitive behavior in small regional markets. Morrison Paul [4] and Driscoll, et al. [20] estimate packers' market power in the fed cattle procurement market and in the beef wholesale market, respectively, using plant-level data but find no market power exertion. Driscoll, et al. [20] indicate that the NEIO model based on conjectural variation coefficients may not be appropriate to estimate packers' market power because the model assumes packers' static profit-maximizing behavior. The study suggests that one needs to a construct more appropriate model beyond the static model (e.g., dynamic behavioral model).

Many earlier studies show that aggregation bias occurs when data are aggregated at a higher level than the analysis level because data aggregation can cause the loss of information [31–34]. Pesaran, et al. [31] propose a hypothesis test of perfect aggregation where aggregation validity is tested on either coefficient equality or the stability of the composition of regressors across micro units over time. The study tests aggregation bias with two levels of aggregation—23 industries and 40 industries in the U.K.—and find, in most cases, very strong bias from aggregate models. Lang and Pearson-Merkowitz [33] examine aggregation bias in estimates of voter preferences and find that commonly used aggregate data yield biased estimates. Their results show large differences between preference estimates from aggregate data and those from exit polls. Lozada [34] derives aggregation bias in estimating Almost Ideal Demand System models with publicly available aggregate data under the assumption of a representative consumer. Results from this study show how restrictive and implausible the assumption is, particularly when the model is estimated with highly aggregated data. Wang, et al. [35] also show that estimates are sensitive to the level of data aggregation. They find that the relationship between the natural resource of a country and its public debt becomes negative with aggregate data when it was positive with disaggregate data. The study concludes that aggregation bias may lead to incorrect estimates, and policy makers may be misled by the incorrect evidence from the aggregate model.

Such studies argue that the estimation of econometric models with typically available aggregate data leads to biased results because the assumption of a representative consumer's utility maximization or producer's profit maximization is not realistic and disregards the heterogeneity of individual behavior [33,34,36]. However, most data, particularly publicly available data, are available in aggregate form, and individual store/firm or household data are rarely available or are expensive (e.g., AC Nielsen and IRI data). Therefore, there have been studies that attempt to combine limited information about individual data (e.g., income distribution, age of household head, number of household members, and residential area) that are available publicly with aggregate data. For example, Berndt, et al. [37] use aggregated data to estimate a demand function but incorporate the probability density function of individual income in the model. Deaton and Muellbauer [38] add a variable representing household heterogeneity to an aggregate demand function. Jorgenson [39] and Stoker [40] also include dummy variables categorizing individual characteristics in demand equations along with aggregate data. Most recently, Wang, et al. [41] propose a procedure that can reduce aggregation bias given minimal information on historical price data (e.g., average price and price dispersion). Their procedure uses the weighted average price over simple average price for data aggregation to reduce aggregation bias, and they find that this debiasing procedure can recover the true parameters asymptotically. Schrammel and Schreiber [42] find that estimates tend to be smaller from an aggregate model than from a disaggregate model and propose a weighted average procedure to reduce aggregation bias. They find that estimates from the weighted average procedure are on average larger than those from an aggregate model.

Our study estimates the aggregation bias empirically using simulated data and, following Berndt, et al. [37] and Stoker [40], shows how bias reduction approaches can be applied for market power estimation models. To the best of our knowledge, no studies have applied these approaches when estimating market power exertion using the NEIO models.

3. Materials and Methods

Various methodologies have been developed to estimate market power exertion in the industrial organization literature. Recently, the NEIO approach has been most frequently used, among others. The NEIO models improve earlier models, particularly structure–conduct –performance models, by estimating structural multi-equations to account for the potential endogeneity problem of market structure (concentration) and conduct (market power). The NEIO models can also be used to infer a price–cost margin by estimating firms' (or industries') cost function using input price data when firm-level cost data are not available. In this section, we first show the data aggregation bias one can face in estimating the market power parameter of the NEIO model when industry-level data are used instead of firm-level data. Then, three hybrid models are derived to show how to reduce the aggregation problem.

3.1. Data Aggregation Problem

The NEIO approach typically estimates a set of structural equations that include output demand (or raw material supply) equations, a price-margin equation derived from an individual firm's profit maximization problem, and input demand equations. Our study focuses on the data aggregation problem in estimating oligopsony power in the U.S. beef packing industry, assuming that packers' raw material procurement market is not competitive but output and other input markets (for capital, labor, and all other intermediate inputs) are competitive. For the sake of brevity and the clarity of our presentation, in this study we only concentrate on the data aggregation problem associated with an estimate of the market power parameter (i.e., conjectural variation elasticity that is defined as the ratio of percent change in industry output to percent change in own firm's output) that is estimated in the price-margin equation.

Consider a profit maximization problem for the *i*th packer,

$$Max_{y_i}\, \pi_i = \{P - w_{Ri}(y)\}y_i - c(y_i, v),$$

where P and w_{Ri} are output and raw material input prices, respectively; industry output y is the sum of the individual firm's output y_i, i.e., $y = \sum_{i=1}^{n} y_i$, c is the processing cost; and v is a vector of input price except raw material price. Then, from the first order condition of the profit maximization problem, we obtain the price-margin equation with the trans-log cost function as:

$$P - w_{Ri} = \frac{w_{Ri}}{\eta_i}\theta_i + \frac{c_i}{y_i}\left(\beta_i + \beta_{Ki}\log w_{Ki} + \beta_{Li}\log w_{Li} + \beta_{Mi}\log w_{Mi} + 2\beta_{yi}\log y_i\right), \quad (1)$$

where $\eta_i = \frac{\partial y_i}{\partial w_{Ri}}\frac{w_{Ri}}{y_i}$ and $\theta_i = \frac{\partial y}{\partial y_i}\frac{y_i}{y}$ are the price elasticity of material input supply and the conjectural variation elasticity of the *i*th firm, respectively, and w_{Ki}, w_{Li}, and w_{Mi} are prices of capital (K), labor (L), and intermediate inputs (M) for firm i, respectively. Here, the estimated conjectural variation elasticity (θ_i) represents the degree of market power, where $\theta_i = 0$ and $\theta_i = 1$ indicate perfect competition and monopsony, while $\theta_i = (0, 1)$ indicates oligopsony. Then, multiplying the market share of each firm to Equation (1) and summing over all firms in the industry can result in the industry-level price-margin equation:

$$P - w_R = \frac{w_R}{\eta}\theta + \frac{1}{y}\sum_{i=1}^{n} c_i\left(\beta_i + \beta_{Ki}\log w_{Ki} + \beta_{Li}\log w_{Li} + \beta_{Mi}\log w_{Mi} + 2\beta_{yi}\log y_i\right). \quad (2)$$

Note that Equation (2) includes industry-level variables, w_R, η, θ, and marginal cost (the second term of the right-hand side of Equation (2)) that are an individual firm's market share weighted averages of firm-level variables and marginal cost from Equation (1).

Therefore, Equation (2) should be a proper way of aggregation to derive the industry-level price-margin equation.

However, it is a common practice to estimate the conjectural elasticity with aggregated data, such as industry level data [10,43,44], because the firm-level data, particularly firm-level marginal cost data (and also capital, labor, and intermediate input prices), are typically not available. The industry-level price (both input and output prices) data are price indices or, at best, unit values that are generally calculated by dividing the total cost with total units used. This approach has critical limitations, such as the assumption that all packers have the same conjectural elasticity and also have identical marginal processing costs ($\theta = \theta_i = \theta_j,\ mc = mc_i = mc_j$). The beef packing industry is capital intensive and is one of the economies of scale industries. The top four packers (Tyson, JBS USA, Cargill, and National) were responsible for 85% of total commercial steer and heifer slaughter in 2020. These large packers' production capacities and quantities are quite different from the rest of packers, and their marginal costs are also different from small-sized packers. Therefore, the conjectural elasticity estimated using aggregated data without properly accounting for individual firms' heterogeneity, particularly in conjectural variation elasticities and marginal costs, is likely to be biased.

Then, the price-margin equation representing this common practice under the assumption of identical conjectural elasticity and marginal cost is:

$$P - W_R = \frac{W_R}{H}\Theta + \frac{C}{y}\{B + B_K \log W_K + B_L \log W_L + B_M \log W_M + 2B_y \log y\}, \tag{3}$$

where the variables and parameters in uppercase letters represent industry level data and corresponding parameters; for example, Θ is the conjectural elasticity estimated with industry data, W_R, W_K, W_L, and W_M are raw material (cattle), capital, labor, and intermediate input prices, respectively, for the U.S. beef packing industry, and C is the total cost of producing industry output y, i.e., $C = \sum_u W_u X_u$, u = K, L and M, and X_u represents input quantities.

Comparing Equations (2) and (3) indicates that one can obtain biased estimates of conjectural elasticity when she estimates Equation (3) instead of Equation (2). To further illustrate the impact of data aggregation on the conjectural elasticity estimate, we derive the aggregation bias analytically as Theil [32], Chung and Kaiser [45]:

$$\begin{aligned} \theta - \Theta \ &= -\sum_{i=1}^{n}\left[h_{i1}^a\beta_i + h_{i2}^a\theta_i + h_{i3}^a\beta_{Ki} + h_{i4}^a\beta_{Li} + h_{i5}^a\beta_{Mi} + h_{i6}^a\beta_{yi}\right] \\ &-\left[\frac{1}{\bar{c}n}\sum_{i=1}^{n}(c_i - \bar{c})\left(h_{i1}^b\beta_i + h_{i2}^b\theta_i + h_{i3}^b\beta_{Ki} + h_{i4}^b\beta_{Li} + h_{i5}^b\beta_{Mi} + h_{i6}^b\beta_{yi}\right)\right] + \left[\frac{1}{n}\sum_{i=1}^{n} r_i\right], \end{aligned} \tag{4}$$

where h_{im}^a is element of $(X'X)^{-1}X'\frac{1}{n}X_i$, and $m = 1, \ldots, 6$, h_{im}^b is element of $(X'X)^{-1}X'(X_i - X^c)$, r_i is element of $(X'X)^{-1}X'S^g B^a$ (see Appendix A for detailed derivation and description of X, X_i, and S^g). Equation (4) shows that the aggregation bias can be decomposed into three parts. The first term in the right-hand side of Equation (4) represents the heterogeneity of firms' conjectural elasticity. As indicated earlier, the aggregate model, Equation (3), assumes an identical conjectural elasticity due to the lack of firm-level data. However, the first term shows that ignoring the heterogeneity (represented by h_{im}^a) of individual firms' conjectural elasticity leads to biased estimates. The second term is formed by ignoring the heterogeneity of firms' costs. The aggregate model also assumes that all firms have equal costs (w_{ui} = w_{uj}, for u = K, L and M, $i \neq j$), ignoring the heterogeneity of firm costs, which leads to biased estimates. The last term represents the bias generated from improper data aggregation (using arithmetic means instead of geometric means).

Equation (4) clearly shows that the difference between θ from (2) and Θ from (3) represents the aggregation bias caused by industry-level data. Following earlier NEIO studies (e.g., [22–24,44,46,47]), we estimate firm- and industry-level market power estimates, θ and Θ, from a system of equations that include a price-margin equation, factor demand equations, and a supply equation (see Appendix B for the system of equations used in this study).

3.2. Approaches to Reduce Data Aggregation Problem

As indicated in the previous section, the best approach to avoid aggregation bias in estimating the market power is to use firm-level data. However, the firm-level data are rarely available, particularly for public use. Therefore, there have been various attempts to reduce aggregation bias in estimating consumer demand, mostly by incorporating limited individual micro data into aggregate models; these models are considered hybrid models [37,38,40,48]. For example, Berndt, et al. [37], Deaton and Muellbauer [38], and Deaton and Muellbauer [48] introduce hybrid approaches that directly incorporate limited individual-level micro data or distribution information into aggregate demand equations. These studies use aggregate data for all dependent and explanatory variables except income variable. They incorporate individuals' income data or income distribution information directly into the aggregate model. Similarly, Jorgenson, et al. [49], Stoker [40], and Jorgenson, et al. [50] incorporate consumer data such as individuals' expenditure or demographic characteristic information into demand equations. Following earlier studies, Berndt, et al. [37] and Stoker [40], our study considers three hybrid models: (1) combining available micro data with aggregate data, (2) combining the distribution information of micro data with aggregate data, and (3) combining the entropy measure of micro data with aggregate data.

3.2.1. Combining Available Micro Data with Aggregate Data

Following Berndt, et al. [37] and Deaton and Muellbauer [38], we combine each packer's production data with other industry-level macro data to estimate the NEIO market power model for the U.S. beef packing industry. Individual packers' production data are generated using Monte Carlo simulations based on publicly available aggregate data. The data generation process will be discussed in more detail in the data section. Then, assuming that one has firm-level beef production data, while all other variables available for her are aggregate data, e.g., $y_i \neq y_j$ but $w_{xi} = w_{xj}$, $x = K, L, M$, and $i \neq j$, Equation (3) can be rewritten as:

$$P - W_R = \frac{W_R}{H}\theta^F + \frac{C}{\overline{y}}\{B + B_K \log W_K + B_L \log W_L + B_M \log W_M + 2B_y \log \overline{y}^g\}, \quad (5)$$

where $\overline{y}$ and $\overline{y}^g$ are arithmetic and geometric means of y_i and θ^F is the conjectural elasticity estimated by macro data and firms' production data. Equation (5) uses the geometric mean because $\log \overline{y}^g$ is the exact representation of the mean of $\log y_i$ when the firm-level output data are available, i.e., $E(\log y_i) = \frac{1}{n}\sum_{i=1}^{n} \log y_i = \log \prod_{i=1}^{n} y_i^{\frac{1}{n}} = \log \overline{y}^g$.

3.2.2. Combining Information of Micro Data Distribution with Aggregate Data

When firm-level output data are not available but the distribution of firm-level output is available, the distribution information can be used along with already available aggregate data [40]. We assume the distribution of packers' outputs follows the gamma distribution with $y_i \sim \Gamma(\alpha_1, 1/\alpha_2)$, following Schons, et al. [51] and Sellman, et al. [52]. Then, Equation (3) can be restated as:

$$P - W_R = \frac{W_R}{H}\theta^D + \frac{C\alpha_2}{\alpha_1}\{B + B_K \log W_K + B_L \log W_L + B_M \log W_M + 2B_y(\psi(\alpha_1) + \log(\alpha 2))\}, \quad (6)$$

where θ^D is the conjectural elasticity estimated with the distribution of packers' output, $\log \overline{y}^g = \psi(\alpha_1) + \log(\alpha_2)$, where $\psi(\alpha_1)$ is the digamma function [53] and $\overline{y}_t = \alpha_1/\alpha_2$ [54,55]. The digamma function, $\psi(\alpha_1)$, is characterized as the natural logarithm of the derivative of the gamma function as $\psi(\alpha_1) = d\log\Gamma(\alpha_1)/d(\alpha_1) = \Gamma'(\alpha_1)/\Gamma(\alpha_1)$ and is asymptotically expanded to $\psi(\alpha_1) \approx \log \alpha_1 - \frac{1}{2}\alpha_1$ [55], and values of α_1 and α_2 were calculated using the method of moments of gamma distribution, i.e., $\alpha_1 = E[y]^2/\mathrm{V}[y]$, $\alpha_2 = E[y]/\mathrm{V}[y]$ [56].

3.2.3. Combining Entropy Measure of Micro Data with Aggregate Data

One can use the entropy of output to represent firm heterogeneity in output. When proxy data for firm output, e.g., plant capacity information or one-year production data at the firm-level, are available (while firm-level data are not available for the entire study period), an entropy measure is calculated from the proxy data and can be incorporated to replace aggregate data [32,37,38,40]. Our study uses the entropy of packer capacity to include the output heterogeneity across packers [57]. Then, Equation (3) can be rewritten with an entropy term as:

$$P - W_R = \frac{W_R}{H}\theta^E + \frac{C}{\bar{y}}\left\{ B + B_K \log W_K + B_L \log W_L + B_M \log W_M + B_y \frac{2C}{n} \frac{\sum_{i=1}^{n} T_i \log T_i}{\sum_{i=1}^{n} T_i} \right\}, \quad (7)$$

where θ^E is the conjectural elasticity estimated with an entropy measure of micro data combined with aggregate data and $\sum_{i=1}^{n} T_i \log T_i / \sum_{i=1}^{n} T_i$ is the Theil's entropy statistic [32], constructed using firm's production capacity, T_i.

Earlier studies consider both household expenditure data and demographic information to address individual heterogeneity in estimating consumer demand. However, due to data limitation and for brevity, it is assumed in our study that individual packers' heterogeneity is represented only by output. Equations (5)–(7) have been derived using the trans-log cost function. However, the use of alternative functional forms may affect estimates of conjectural elasticity [24,58]. We conduct a sensitivity analysis with generalized Leontief and normalized quadratic functions. Derivations of Equations (5)–(7) with these two alternative functional forms are available upon request.

3.3. Data

Our study generates firm-level data using Monte Carlo simulations to estimate firm and industry models as well as models that are designed to reduce aggregation bias. The simulations generate one thousand firm-level data sets where each data set has three hundred and sixty monthly observations. To generate the firm-level data, we first estimate system equations for the U.S. beef packing industry (see Appendix B for specifications of the equations) using publicly available industry data to obtain parameter estimates and the corresponding variance–covariance matrix. The estimated parameters and variance–covariance matrix that are used as the design matrix to generate firm-level data are reported in Appendix B (Tables A1 and A2). Given information from the design matrix and exogenous and endogenous variables from the industry data, one thousand firm-level data sets are simulated repeatedly for each month for thirty years. A stochastic simulation is conducted in this process by assuming additive multivariate normal errors for each structural equation of endogenous variables. For aggregate data, outputs from one thousand firms are aggregated for each month, while arithmetic mean was calculated for all price and cost data.

Data used for the Monte Carlo simulations were compiled from various reports published by the U.S. Department of Agriculture (USDA) and the U.S. Department of Labor (USDL) for 30 years from January 1980 to December 2009. Retail and wholesale prices for beef were from *Meat Price Spreads* (USDA/ERS) [59]. Steer and heifer slaughter quantities were obtained from *Livestock Slaughter Annual Summary* (USDA/NASS) [60]. Retail output refers to the aggregate commercial beef production in the U.S. from *Red Meat Yearbook* (USDA/ERS) [61]. The Herfindahl Hirschman Index, used for the generalized Leontief function, was collected from *Packer and Stockyards Programs Annual Reports* (USDA/AMS) [1]. Price and productivity data for capital, labor, and material inputs were obtained from *Industry Productivity and Cost Database* USDL [62]. Input demands for capital, labor, and intermediate goods were calculated using the product of steer and heifer slaughter quantity and wholesale price divided by each productivity index following Park and Bera [63]. Calf and corn prices were obtained from *Nebraska Statistics* USDA [64] and *Feed Grains Database* USDA [65], respectively. Fuel price is the consumer price index of gasoline from USDL [62]. Prices of calf and corn are deflated by the producer price index from USDL [62], while fuel price is deflated by the consumer price index from USDL [62]. Descriptive statistics of variables used for Monte Carlo simulations are presented in Table 2.

Table 2. Descriptive Statistics of Variables Used for Monte Carlo Simulations.

	Mean	S.D.	Median	Maximum	Minimum
HHI for steer and heifer slaughter	0.16	0.05	0.18	0.21	0.06
Steers and Heifer Slaughter (bil. lbs)	2.73	0.22	2.72	3.32	2.23
Beef Retail Price ($/cwt)	119.74	15.82	118.83	156.41	92.23
Beef Wholesale price ($/cwt)	80.05	3.3012	79.21	92.31	73.93
Capital Price (2000 = 100)	78.37	20.53	76.92	111.85	45.92
Labor Price (2000 = 100)	88.88	27.14	85.41	138.92	44.26
Material Price (2000 = 100)	100.83	21.26	100.24	159.97	70.5
Capital Productivity (2000 = 100)	102.25	1.7342	102.4	105.62	99.58
Labor Productivity (2000 = 100)	97.04	8.1391	97.61	112.85	83.57
Intermediate Input Productivity (2000 = 100)	90.56	7.8708	90.99	102.57	78.18
Calf Price ($/cwt)	88.70	14.24	89.33	127.51	43.89
Corn Price ($/bushel)	2.27	0.42	2.25	3.39	1.49
Fuel Price ($/gal)	1.37	0.36	1.22	2.80	0.89

4. Results

Following previous studies in the literature (e.g., [43,66]), we estimate a system of equations that include price-margin, factor demand, and raw material supply equations (see Appendix B) using the General Moment Methods (GMM) procedure. The instrumental variables approach is used to address the endogeneity problem in the system. The instrumental variables include HHI for cattle slaughter [1], CR4 for steer and heifer slaughter [1], steer and heifer price and quantity in the Nebraska and Texas markets [67], cattle on feed [68], cattle placement [68], cattle on marketing [68], retail prices of pork and chicken [68], and per capita income [60].

Table 3 presents the aggregation bias we estimated using the simulated data. As indicated earlier, we calculated the bias by subtracting the conjectural elasticity estimate of the aggregate model (Θ) from the firm-level estimate (θ). Firm-level estimates and standard errors are the market share weighted mean of one thousand firms for the three hundred and sixty months of the study period and corresponding standard errors. From all three functional forms, the aggregation biases are positive, indicating that aggregate models provide smaller estimates than the firm-level models. All estimates of conjectural elasticities are statistically significant at the 1% level. Conjectural elasticity estimates from both firm and aggregate models are sensitive to functional forms, resulting in a different level of aggregation bias by functional form. For example, the estimate from a firm-level model with trans-log cost function is 0.1712, while the estimate from an aggregate model is 0.1464, resulting in aggregation bias at 0.0248. When the generalized Leontief function is used for the cost function, the estimates become 0.1536 and 0.1099 from firm-level and aggregate models, respectively, increasing the bias to 0.0437. With the normalized quadratic cost function, the bias jumps to an even higher level, 0.1524. The bias estimates are all statistically significant at the 1% level.

Table 3. Aggregation Bias: Firm-level Model vs. Aggregate Model.

Model	Trans-Log	Generalized Leontief	Normalized Quadratic
Firm-level Model (θ)	0.1712 *** (0.0024)	0.1536 *** (0.0004)	0.2332 *** (0.0040)
Aggregated Model (Θ)	0.1464 *** (0.0075)	0.1099 *** (0.0021)	0.0808 *** (0.0185)
Aggregation Bias ($\theta - \Theta$)	0.0248 *** (0.0079)	0.0437 *** (0.0021)	0.1524 *** (0.0189)

Numbers in parentheses are standard errors. *** Indicates significant at the 1% level.

Our results indicate that models estimated using industry-level aggregate data tend to underestimate market power exertion in the U.S. beef packing industry. Considering that many previous studies estimated the market power exertion parameter, conjectural elasticity, using the industry-level data, these studies could have underestimated the market power exertion in the U.S. beef packing industry.

Table 4 compares results from hybrid models with estimates of the firm-level model to show if the hybrid models can improve the aggregation bias problem. The three approaches used for the hybrid models include combining industry-level data with (I) available firm-level data (individual packers' output data), (II) information about the distribution of firm data (the distribution of packers' output data), and (III) the entropy measure of firm-level data (the entropy of individual packers' capacity data). All estimates from hybrid models are statistically significant at the 1% level and show the improvement of aggregation bias problem. However, substantial aggregation bias still remains with statistical significance at least at the 10% level in most cases. For example, with the trans-log functional form, the initial aggregation bias, 0.0248, reported in Table 4, has been reduced to 0.0164, 0.0117 and 0.0220 by using (I), (II), and (III), respectively. Similar results with a small reduction in bias (the biases are still statistically significant at the 1% level) are found under the other two functional forms, with one exception. When the generalized Leontief cost function is used for the entropy approach (III), the bias was not statistically significant, mostly due to the large standard error of the conjectural elasticity from III. All other parameter estimates of system equations for aggregate and hybrid models are reported in Appendix C.

Table 4. Aggregation Bias: Firm-level Model vs. Hybrid Models.

Model	Trans-Log	Generalized Leontief	Normalized Quadratic
Firm level Model (θ)	0.1712 *** (0.0024)	0.1536 *** (0.0004)	0.2332 *** (0.0040)
Combining Available Micro data (θ^F) (I)	0.1548 *** (0.0085) [0.0164] *	0.1008 *** (0.0039) [0.0528] ***	0.0907 *** (0.0211) [0.1425] ***
Combining Distribution Information of Micro Data (θ^D) (II)	0.1595 *** (0.0068) [0.0117] *	0.1147 *** (0.0026) [0.0389] ***	0.1047 *** (0.0228) [0.1285] ***
Combining Entropy Measure of Micro Data (θ^E) (III)	0.1492 *** (0.0089) [0.0220] **	0.1119 *** (0.0349) [0.0417]	0.0888 *** (0.0308) [0.1444] ***

Numbers in parentheses and brackets are standard errors and aggregation bias, $\theta - \theta^i$, $i = F, D$, and E, respectively. *, **, *** Indicate significant at 10%, 5% and 1% levels, respectively.

Two econometric tests, the Wald Chi-square test and the Sargan–Hansen overidentification test, are conducted in this study to show model validity, and the results are reported in Table 5. The Wald test examines the overall significance of slope coefficients, and extremely low p-values, smaller than 0.0001, in Table 5 indicate good model fit to the data for all four models. The Sargan–Hansen test checks over-identifying restrictions of the instrument variables used for estimation. The test also follows an asymptotic Chi-square distribution, and if the null hypothesis of all valid instrumental variables is not rejected, we can state that the instrumental variables used in the study are reliable, which can support the reliability of estimation results [69,70]. Test statistics and corresponding *p*-values show the failure of rejecting the null hypothesis for all models, which supports the validity of our instrumental variables.

Table 5. Test for Model Validity.

Model	Test	Trans-Log		Generalized Leontief		Normalized Quadratic	
		Statistic	**Prob**	**Statistic**	**Prob**	**Statistic**	**Prob**
Aggregated Model	Wald	2087.2	<0.0001	12,405.0	<0.0001	60.1	<0.0001
	Sargan-Hansen	70.4	0.4638	90.5	0.107	84.7	0.1118
Combining Available Micro data	Wald	2112.6	<0.0001	8666.8	<0.0001	54.9	<0.0001
	Sargan-Hansen	70.8	0.4511	90.6	0.1056	84.0	0.1216
Combining Distribution Information of Micro Data	Wald	1992.2	<0.0001	11,872.0	<0.0001	70.4	<0.0001
	Sargan-Hansen	76.2	0.2873	86.7	0.1669	82.2	0.1510
Combining Entropy Measure of Micro Data	Wald	2021.5	<0.0001	222.4	<0.0001	51.9	<0.0001
	Sargan-Hansen	73.3	0.3397	89.6	0.1049	82.6	0.1265

5. Discussion

Our study investigated data aggregation bias in estimating market power in the U.S. beef packing industry and attempted to reduce the bias using a few empirical procedures proposed in the literature. The aggregation bias was estimated by comparing conjectural variation elasticities estimated from firm- and industry-level models using simulated data. Hybrid models, combining limited firm-level data with aggregate data, were also estimated to illustrate whether they can reduce aggregation bias. All econometric models were estimated with three alternative functional forms of cost function for sensitivity analysis.

Our results showed that aggregate models with industry-level data underestimated market power exertion in the U.S. beef packing industry and aggregation bias was statistically significant at the one percent level. Estimates of hybrid models indicated that they did not effectually remove the aggregation bias. Our results also showed that market power estimates and aggregation bias were sensitive to alternative forms of cost function. Our findings raise awareness regarding aggregation bias in estimating market power and suggest that market power estimates from aggregate models may be misleading. A similar conclusion was drawn from a recently published article by Carpenter, et al. [71]. The study compares econometric estimates from different levels of industrial aggregation using data from the Federal Statistical Research Data Center and finds significant aggregation bias.

Beef packing is a highly concentrated industry, with 85% of the concentration ratio belonging to the four largest packers in purchasing beef cattle. As high concentration is typically linked to low competition and low producer price, a flurry of studies has investigated packers' market power exercise in the beef cattle market but has found limited evidence of the market power effect in reducing producer prices. However, as presented in Table 1, most studies estimating beef packers' market power used aggregate data mostly ignoring individual packers' heterogeneous business behavior and competition in regional markets. Our findings indicate that the limited evidence of packers' market power exertion could be due to data aggregation. Findings from earlier studies could have understated the market power effect due to the data aggregation problem. We conclude that studies relying on aggregate data may provide misleading results and suggest that researchers use fewer aggregate data and make extra effort to reduce the data aggregation problem.

The limited impact of the bias reduction effort through the hybrid models could be due to the limited information available regarding firm-level data. Our efforts were applied only to the beef production data. If more data or information were available, we could have found a more significant effect on reducing the bias. For example, Berndt, et al. [37] estimate a demand function using a hybrid model with the income distribution data but fail to reduce the aggregation bias. However, recent studies incorporating extended information about micro-level data show better results (e.g., [39,72,73]). For example, Miller and Alberini [73] use individual-level data such as household level information, housing structure information, and household capital stock and income data along with available aggregate data to estimate a demand equation and show significant improvement in reducing the aggregation bias.

Our findings are based on a simulated dataset generated with a set of parameters and the variance–covariance matrix reported in Appendix B. Therefore, a question arises as to whether our findings are generalizable with alternative sets of parameters and an alternative variance–covariance matrix. To answer this question, one can estimate aggregation bias with a large number of datasets generated from an alternative set of parameters and variance–covariance matrix, particularly from alternative parameters and variance–covariances related to the market power parameter. Another direction for future research might be to extend our hybrid model by incorporating more variables reflecting heterogeneity in firm behavior. Our study included only individual firms' production and production capacity data, which could have resulted in a limited impact on reducing data aggregation bias.

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Appendix A

Derivation of Equation (4)

The conjectural elasticity in Equation (2) is;

$$\theta = \sum_{i=1}^{n} s_i \theta_i, \text{ where } s_i = y_i / y. \tag{A1}$$

Then, Equation (A1) can be rewritten by the definition of covariance, $cov(a,b) = E(ab) - E(a)E(b)$ as:

$$\sum_{i=1}^{n} s_i \theta_i = n\mathrm{cov}(s_i, \theta_i) + \Theta. \tag{A2}$$

Similarly, the first term in parenthesis of Equation (2) can be rewritten as:

$$\sum_{i=1}^{n} c_i \beta_i = n\mathrm{cov}(c, \beta) + ncB. \tag{A3}$$

The second term in parenthesis of Equation (2) can be restated using $E(abc) = cov(ab,c) + E(c)cov(a,b) + E(a)E(b)E(c)$

$$\sum_{i=1}^{n} c_i \beta_{Ki} \log w_{Ki} = n\mathrm{cov}(c, \beta_K \log w_K) + n\bar{c}\mathrm{cov}(\beta_K, \log w_K) + n\bar{c}B_K \log w_K^g \tag{A4}$$

The other terms in the parenthesis can be restated similarly, then Equation (2) can be rewritten as:

$$\begin{aligned} P - w_R = {} & \tfrac{w_R}{\eta}\{n\mathrm{cov}(s_i, \theta_i) + \Theta\} + \tfrac{n\bar{c}}{y}\left\{B + B_K \log w_K^g + B_L \log w_L^g + B_M \log w_M^g + B_y \log y^g\right\} \\ & + \tfrac{n\bar{c}}{y}\{\mathrm{cov}(\beta_K, \log w_K) + \mathrm{cov}(\beta_L, \log w_L) + \mathrm{cov}(\beta_M, \log w_M) + \mathrm{cov}(\beta_y, \log y)\} \\ & + \tfrac{n}{y}\{\mathrm{cov}(c, \beta_y) + \mathrm{cov}(c, \beta_K \log w_K) + \mathrm{cov}(c, \beta_L \log w_L) + \mathrm{cov}(c, \beta_M \log w_M) + \mathrm{cov}(c, \beta \log y)\} \end{aligned} \tag{A5}$$

where w_u^g, w_L^g, w_M^g and y^g is geometric mean of w_K, w_L, w_M and y.

By multiplying $y/n\bar{c}$ to both sides of (A5), where $c = \sum c_i$, $\bar{c} = \sum c_i/n$ and using Theil [32],

$$\begin{aligned} \log w_I^g &\approx \log \overline{w}_I - \tfrac{1}{2n}\sum\left(\log w_{Ii} - \log w_I^g\right)^2, \ I = K, L, M \\ \log y^g &\approx \log \overline{y} - \tfrac{1}{2n}\sum\left(\log y_i - \log y^g\right)^2, \end{aligned}$$

we have,

$$\begin{aligned} \tfrac{(P-w_R)y}{n\bar{c}} = {} & \tfrac{w_R}{\eta\bar{c}}\overline{y}\,\Theta + \left(B + B_K \log W_K + B_L \log W_L + B_M \log W_M + B_y \tfrac{1}{2} \log y\right) \\ & + \left\{\mathrm{cov}\left(\tfrac{w_R}{\eta\bar{c}} y_i, \theta_i\right) + \sum_u \mathrm{cov}(\beta_u, \log u)\right\} + \tfrac{1}{\bar{c}}\left\{\mathrm{cov}(c_i, \beta_i) + \sum_u \mathrm{cov}(c_i, \beta_{ui} \log u_i)\right\} \\ & - \tfrac{1}{2n}\left\{\sum_u \sum_{i=1}^{n} \beta_u (\log u_i - \log u^g)^2\right\}, \end{aligned} \tag{A6}$$

where u_i is w_K, w_L, w_M and y.

For convenience and brevity, we rewrite (A6) in matrix form following Chung and Kaiser [45] as:

$$Y = XB^a + \xi \tag{A7}$$

where $Y = \frac{(P-w_R)y}{n\bar{c}}$, $\xi = \frac{1}{n}\sum\limits_{i=1}^{n}(X_i - X)\left(\beta_i^a - B^a\right) + \frac{1}{\bar{c}n}\sum\limits_{i=1}^{n}\left\{(X_i - X^c)\beta_i^I - (X - X^c)B^I\right\}\left(C_i - \overline{C}\right) - \frac{1}{n}\sum\limits_{i=1}^{n} S^g B^a + \varepsilon$.

Here, we have:

$$X = \begin{bmatrix} 1 & \frac{w_R}{\eta\bar{c}}\overline{y} & \log W_K & \log W_L & \log W_M & \log y \\ 1 & \frac{w_R}{\eta\bar{c}}\overline{y} & \log W_K & \log W_L & \log W_M & \log y \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \frac{w_R}{\eta\bar{c}}\overline{y} & \log W_K & \log W_L & \log W_M & \log y \end{bmatrix}, X_i = \begin{bmatrix} 1 & \frac{w_R}{\eta\bar{c}} y_1 & \log w_{K1} & \log w_{L1} & \log w_{M1} & \log y_1 \\ 1 & \frac{w_R}{\eta\bar{c}} y_2 & \log w_{K2} & \log w_{L2} & \log w_{M2} & \log y_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \frac{w_R}{\eta\bar{c}} y_i & \log w_{Ki} & \log w_{Li} & \log w_{Mi} & \log y_i \end{bmatrix}, X^c = \begin{bmatrix} 0 & \frac{w_R}{\eta\bar{c}} y_1 & 0 & 0 & 0 & 0 \\ 0 & \frac{w_R}{\eta\bar{c}} y_2 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \frac{w_R}{\eta\bar{c}} y_i & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$S^g = \begin{bmatrix} 0 & 0 & \left(\log w_{K1} - \log w_K^g\right)^2 & \left(\log w_{L1} - \log w_L^g\right)^2 & \left(\log w_{M1} - \log w_M^g\right)^2 & (\log y_1 - \log y^g)^2 \\ 0 & 0 & \left(\log w_{K2} - \log w_K^g\right)^2 & \left(\log w_{L2} - \log w_L^g\right)^2 & \left(\log w_{M2} - \log w_M^g\right)^2 & (\log y_2 - \log y^g)^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \left(\log w_{Ki} - \log w_K^g\right)^2 & \left(\log w_{Li} - \log w_L^g\right)^2 & \left(\log w_{Mi} - \log w_M^g\right)^2 & (\log y_i - \log y^g)^2 \end{bmatrix}, B^a = \begin{bmatrix} B \\ \Theta \\ B_K \\ B_L \\ B_M \\ B_y \end{bmatrix}, \beta^a = \begin{bmatrix} \beta \\ \theta \\ \beta_K \\ \beta_L \\ \beta_M \\ \beta_y \end{bmatrix}, \beta_i^a = \begin{bmatrix} \beta_i \\ \theta_i \\ \beta_{Ki} \\ \beta_{Li} \\ \beta_{Mi} \\ \beta_{yi} \end{bmatrix},$$

where $B^I = B^a \cdot I$, $\beta_i^I = \beta_i^a \cdot I$, I is a (6×6) identity matrix, $\overline{C}$ and C_i are (6×1) column vectors, where each vector has same elements $\bar{c}$ and c_i, respectively.

The error term of Equation (A7) can be expanded to:

$$\xi = \frac{1}{n}\sum_{i=1}^{n}(X_i - X)(\beta_i^a - B^a) + \frac{1}{\bar{c}n}\sum_{i=1}^{n}\left(X_i\beta_i^I - XB^I\right)(C_i - \overline{C}) - \frac{1}{\bar{c}n}\sum_{i=1}^{n} X^c\left(\beta_i^I - B^I\right)(C_i - \overline{C}) - \frac{1}{n}\sum_{i=1}^{n} S^g B^a + \varepsilon. \tag{A8}$$

Then, to derive the relationship between θ and Θ, estimator b of parameter B^a from Equation (A7) is calculated as:

$$\begin{aligned} b &= (X'X)^{-1}X'Y = (X'X)^{-1}X'XB^a + (X'X)^{-1}X'\xi \\ &= B^a + \tfrac{1}{n}\sum_{i=1}^{n}\left\{(X'X)^{-1}X'X_i\right\}\beta_i^a + \tfrac{1}{\bar{c}n}\sum_{i=1}^{n}\left\{(X'X)^{-1}X'(X_i - X^c)\beta_i^a(C_i - \overline{C})\right\} - \tfrac{1}{n}(X'X)^{-1}X'\sum_{i=1}^{n}S^g B^a + \varepsilon \end{aligned} \quad \text{(A9)}$$

The unbiasedness property of b yields:

$$E(b) = B^a + \sum_{i=1}^{n} H_i^a \beta_i^a + \frac{1}{\bar{c}n}\sum_{i=1}^{n} H_i^b \beta_i^a (C_i - \overline{C}) - \frac{1}{n}\sum_{i=1}^{n} R_i, \quad \text{(A10)}$$

where $H_i^a = (X'X)^{-1}X'\frac{1}{n}X_i$, $H_i^b = (X'X)^{-1}X'(X_i - X^c)$, $R_i = (X'X)^{-1}X'S^g B^a$.

Matrices, H_i^a, H_i^b and R_i, can be written as:

$$H_i^a = \begin{bmatrix} h_{11}^a & \cdots & h_{16}^a \\ \vdots & \ddots & \\ h_{i1}^a & \cdots & h_{i6}^a \end{bmatrix},\ H_i^b = \begin{bmatrix} h_{11}^b & \cdots & h_{16}^b \\ \vdots & \ddots & \\ h_{i1}^b & \cdots & h_{i6}^b \end{bmatrix},\ R_i = \begin{bmatrix} r_1 \\ \vdots \\ r_i \end{bmatrix},$$

Finally, market power parameters, θ and Θ, elements of vectors, β^a and B^a, can be obtained from Equation (A10) through algebra of matrices, and the aggregation bias $\theta - \Theta$ is derived as:

$$\begin{aligned} \theta - \Theta &= -\sum_{i=1}^{n}\left[h_{i1}^a\beta_i + h_{i2}^a\theta_i + h_{i3}^a\beta_{Ki} + h_{i4}^a\beta_{Li} + h_{i5}^a\beta_{Mi} + h_{i6}^a\beta_{yi}\right] \\ &-\left[\tfrac{1}{\bar{c}n}\sum_{i=1}^{n}(c_i - \bar{c})\left(h_{i1}^b\beta_i + h_{i2}^b\theta_i + h_{i3}^b\beta_{Ki} + h_{i4}^b\beta_{Li} + h_{i5}^b\beta_{Mi} + h_{i6}^b\beta_{yi}\right)\right] + \left[\tfrac{1}{n}\sum_{i=1}^{n} r_i\right]. \end{aligned} \quad \text{(A11)}$$

Appendix B

The NEIO Model for the U.S. Beef Packing Industry

Price-margin equation:

$$P - W_R = \frac{W_R}{H}\Theta + \frac{C}{y}\{B + B_K logW_K + B_L logW_L + B_M logW_M + 2B_y logy\}$$

where $C = \sum_u W_u X_u$ is total cost, W and X represent input prices and quantities, and u = K, L and M.

Factor demand equations for capital (K), labor (L), and intermediate inputs (M):

$$\begin{aligned} X_K &= \tfrac{C}{W_K}\left(B_{K0} + \sum_u B_{Ku}\log W_u + B_{Ky}\log y\right) \\ X_L &= \tfrac{C}{W_L}\left(B_{L0} + \sum_u B_{Lu}\log W_u + B_{Ly}\log y\right) \\ X_M &= \tfrac{C}{W_M}\left(B_{M0} + \sum_u B_{Mu}\log W_u + B_{My}\log y\right), \end{aligned}$$

Raw material supply function:

$$\ln y = A_0 + H\log(catp/S) + A_1\log(cornp/S) + A_2\log(calfp/S) + A_3\log(fuelp/S)$$

where H is price elasticity of material input supply, *catp* is the beef gross farm value, *cornp*, *calfp*, and *fuelp* are farm-level corn and calf prices, and gasoline price (representing transportation cost), respectively, and S is the producer price index for farm products (2000 = 100).

Variance-covariance matrix and parameter estimates used for Monte Carlo simulations

Table A1. Variance-Covariance Matrix Used for Monte Carlo Simulations.

	$P\text{-}W_R$	X_K	X_L	X_M	$\log y$
$P\text{-}W_R$	0.096				
X_K	0.037	0.270			
X_L	−0.017	0.459	0.088		
X_M	−0.005	0.066	0.005	0.033	
$\log y$	0.734	0.033	0.475	0.222	1.952

Table A2. Parameter Estimates Used for Monte Carlo Simulations.

Parameter	Estimate	Parameter	Estimate
B_{K0}	0.284	B_Y	2.890
B_{L0}	0.921	B_K	0.027
B_{M0}	1.542	B_L	−0.57
B_{KK}	0.178	B_M	−1.14
B_{LL}	0.224	Θ	0.019
B_{MM}	0.291	A_0	−3.12
B_{KL}	−0.05	H	0.783
B_{KM}	−0.04	A_1	0.093
B_{LM}	−0.08	A_2	0.166
B	−2.36	A_3	−0.04

Appendix C

Estimates of aggregate and hybrid models are reported in Table A3 (with translog cost function), Table A4 (with generalized Leontief cost function), and Table A5 (with quadratic cost function).

Table A3. Estimates from Translog Cost Function.

Parameters	Aggregated Model		Combining Available Micro Data		Combining Distribution Information of Micro Data		Combining Entropy Measure of Micro Data	
	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.
B_K	−5.5092 ***	0.2049	−5.1923 ***	0.1891	−5.8439 ***	0.2077	−5.3464 ***	0.1949
B_L	3.8037 ***	0.157	3.6278 ***	0.1481	2.4671 ***	0.1273	3.5429 ***	0.1444
B_M	−2.5334 ***	0.0888	−2.8944 ***	0.0966	−2.1516 ***	0.0785	−2.3085 ***	0.0831
B_{KK}	−1.0853 ***	0.2263	−1.0052 ***	0.2117	−1.0849 ***	0.1999	−1.0398 ***	0.2138
B_{KL}	1.1371 ***	0.1886	1.104 ***	0.1821	1.0602 ***	0.1552	1.0828 ***	0.1747
B_{KM}	−0.5532 ***	0.074	−0.5808 ***	0.0782	−0.4687 ***	0.0548	−0.5239 ***	0.0683
B_{LM}	0.153 **	0.0703	0.1636 **	0.0739	0.0933 *	0.0524	0.1267 **	0.0636
B_{LL}	−0.8811 ***	0.1661	−0.8696 ***	0.1647	−0.8066 ***	0.1346	−0.8249 ***	0.1523
B_{MM}	0.1966 ***	0.0659	0.2094 ***	0.0696	0.1916 ***	0.0493	0.2052 ***	0.0588
B	−5.2412	4.107	9.0548 **	4.4112	4.8772	12.7132	25.4635	36.3096
B_K	4.2836 ***	0.1353	4.055 ***	0.1239	4.5181 ***	0.1356	4.1573 ***	0.1269
B_L	−2.5384 ***	0.1057	−2.4097 ***	0.0993	−1.52 ***	0.0848	−2.3403 ***	0.0962
B_M	2.2004 ***	0.0601	2.4718 ***	0.0652	1.9146 ***	0.0534	2.0294 ***	0.0561
B_Y	2.3065	1.4981	4.7329 *	2.4953	0.1054	0.2642	4.3067	2.8616
Θ	0.1464 ***	0.0075	0.1548 ***	0.0085	0.1595 ***	0.0068	0.1492 ***	0.0089
A_0	−2.6567 *	1.3944	−2.7056 **	1.3405	−2.8889 **	1.3678	−2.916 **	1.3818
H	0.8706 ***	0.3159	0.8864 ***	0.3018	0.9095 ***	0.3075	0.9261 ***	0.3114
A_1	0.0984 ***	0.0261	0.0975 ***	0.0256	0.1098 ***	0.0248	0.1039 ***	0.0258
A_2	0.0497 *	0.0271	0.0459 *	0.0268	0.0638 **	0.0278	0.0548 **	0.0276
A_3	−0.0465 ***	0.0093	−0.0459 ***	0.0089	−0.0509 ***	0.0093	−0.0481 ***	0.0092

*, **, *** Indicate significant at 10%, 5% and 1% levels, respectively.

Table A4. Estimates from Price-Margin Equation with Generalized Leontief Cost Function.

Parameters	Aggregated Model		Combining Available Micro Data		Combining Distribution Information of Micro Data		Combining Entropy Measure of Micro Data	
	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.
B_K	0.1204 ***	0.0125	0.0007 ***	0.0002	0.0857 ***	0.0107	0.0007 ***	0.0002
B_L	0.0471 ***	0.0049	−0.0006 ***	0.0001	0.0749 ***	0.0083	−0.0006 ***	0.0001
B_M	0.1149 ***	0.0114	−0.0001	0.0001	0.1179 ***	0.0121	0.0000	0.0001
B_{KK}	4.2361 ***	0.4476	6.3276 ***	0.5754	5.144 ***	0.5778	6.6753 ***	0.5979
B_{KL}	−0.8485 ***	0.0922	−1.2852 ***	0.1416	−1.2088 ***	0.1349	−1.4125 ***	0.1506
B_{KM}	−1.0668 ***	0.1085	−1.3351 ***	0.1506	−1.0601 ***	0.1297	−1.3689 ***	0.155
B_{LM}	0.3774 ***	0.0443	−0.152 **	0.0693	0.2873 ***	0.0578	−0.1059	0.072
B_{LL}	1.2851 ***	0.0909	3.4829 ***	0.3027	2.0516 ***	0.1639	3.627 ***	0.3133
B_{MM}	1.5662 ***	0.1223	3.5415 ***	0.2224	1.7241 ***	0.135	3.5155 ***	0.2175
Θ	0.1099 ***	0.0021	0.1008 ***	0.0039	0.1147 ***	0.0026	0.1119 ***	0.0349
A_0	−3.9864	2.7007	−0.5045	4.0218	−3.0284	2.7292	−1.4958	4.0445
H	1.1451 *	0.6698	0.3662	1.0261	0.9408	0.6921	0.6172	1.0304
A_1	0.1475 ***	0.0478	0.1035	0.0775	0.1289 **	0.0512	0.093	0.08
A_2	0.0831	0.0575	0.0482	0.0967	0.0627	0.0666	0.0341	0.0967
A_3	−0.0675 ***	0.0201	−0.0517	0.0362	−0.0575 ***	0.02	−0.0559	0.0364

*, **, *** Indicate significant at 10%, 5% and 1% levels, respectively.

Table A5. Estimates from Price-Margin Equation with Quadratic Cost Function.

Parameters	Aggregated Model		Combining Available Micro Data		Combining Distribution Information of Micro Data		Combining Entropy Measure of Micro Data	
	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.	Estimate	S. E.
B_K	0.6189 ***	0.1110	0.6171 ***	0.1127	0.6240 ***	0.1093	0.6089 ***	0.1134
B_L	2.7086 ***	0.1539	2.7173 ***	0.1585	2.7340 ***	0.1621	2.7211 ***	0.1618
B_M	3.9995 ***	0.2811	4.0129 ***	0.2880	4.0362 ***	0.2921	4.0249 ***	0.2920
B_{KK}	0.9457 ***	0.1398	0.9427 ***	0.1402	0.9272 ***	0.1434	0.9320 ***	0.1425
B_{LL}	−0.0263	0.0699	−0.0245	0.0704	−0.0292	0.0687	−0.0269	0.0703
B_{MM}	−0.3217	0.1582	−0.3286	0.1610	−0.3394	0.1622	−0.3330	0.1632
B_{KL}	0.0553	0.0552	0.0562	0.0554	0.0620	0.0547	0.0656	0.0558
B_{KM}	0.0790	0.1192	0.0863	0.1204	0.0972	0.1260	0.0928	0.1234
B_{LM}	−0.2041	0.0915	−0.2095	0.0929	−0.2131	0.0927	−0.2176	0.0941
Θ	0.0808 ***	0.0185	0.0907 ***	0.0211	0.1047 ***	0.0228	0.0888 ***	0.0308
B_{yK}	0.0904 ***	0.0168	0.0894 ***	0.0173	0.0869 ***	0.0164	0.0898 ***	0.0167
B_{yL}	0.0188	0.0175	0.0175	0.0182	0.0143	0.0192	0.0172	0.0190
B_{yM}	−0.0430	0.0335	−0.0446	0.0347	−0.0485	0.0368	−0.0461	0.0362
B	−10.4274	2.8562	−11.7006	3.2295	−13.7350	3.4709	−11.6321	5.2415
B_y	0.0826 ***	0.0229	0.0000 ***	0.0000	0.0000 ***	0.0000	0.0000 **	0.0000
A_0	5.2599	3.9154	5.4906	3.8667	5.3870	3.9649	5.0634	3.9947
H	−1.1305	0.9331	−1.1843	0.9228	−1.1585	0.9435	−1.0621	0.9459
A_1	0.0815	0.0757	0.0815	0.0757	0.0839	0.0739	0.0710	0.0759
A_2	0.1746	0.1191	0.1738	0.1186	0.1723	0.1135	0.1558	0.1153
A_3	−0.0936	0.0331	−0.0937	0.0335	−0.0951	0.0325	−0.0947	0.0333

, * Indicate significant at 10%, 5% and 1% level.

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