ESSAYS ON ESTIMATING MARKET POWER EXERTION IN THE U.S. BEEF PACKING INDUSTRY

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
May 2020

ESSAYS ON ESTIMATING MARKET POWER

EXERTION IN THE U.S. BEEF PACKING INDUSTRY

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Date of Degree: MAY, 2020

Title of Study: ESSAYS ON ESTIMATING MARKET POWER EXERTION IN THE U.S. BEEF PACKING INDUSTRY

Major Field: AGRICULTURAL ECONOMICS

Abstract: The first essay discusses the aggregation bias issue in estimating the degree of market power for agricultural and food industries and explores ways to improve the conjectural elasticity estimates using proper aggregation procedures. Aggregation biases, caused by ignoring heterogeneity of micro agents, are derived mathematically, and proper procedures to reduce the aggregation biases are proposed by incorporating public micro level data in the empirical model with their distribution information. Conjectural elasticity is estimated with alternative cost functions for the sensitivity analysis. Overall, the degree of conjectural elasticities from newly developed empirical models tend to show more collusion state of market than those from traditional aggregated models. The conjectural elasticity from the distributional model and joint distribution model has closer value with conjectural elasticity from firm level data.

The second paper examines the impact of captive market supply on spot market price in the U.S. cattle procurement market, while considering dynamic interactions between captive and spot markets. Both conceptual analysis and empirical models explore advantages of dynamic models over static models by focusing on the temporal change in the ratio of captive purchase to packers' total procurement and discount factor. Empirical models were estimated using the Kalman filter procedure with three alternative cost functions. Overall, dynamic estimation results found a negative relationship between captive market quantity and spot market prices. However, results of static model showed that the captive market quantity - spot market price relationship was sensitive to assumptions on captive supply and functional forms of cost function. Findings from our empirical analysis clearly suggest that dynamic models are more appropriate than static models in examining the impact of captive supply on spot price in the cattle procurement market.

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CHAPTER I

ESTIMATING MARKET POWER EXERTION FOR AGRICULTURAL AND FOOD INDUSTRIES: AN ISSUE OF DATA AGGREGATION BIAS REDUCTION

ABSTRACT

This study discusses the aggregation bias issue in estimating the degree of market power for agricultural and food industries and explores ways to improve the conjectural elasticity estimates using proper aggregation procedures. Aggregation biases, caused by ignoring heterogeneity of micro agents, are derived mathematically, and proper procedures to reduce the aggregation biases are proposed by incorporating public micro level data in the empirical model with their distribution information. Conjectural elasticity is estimated with alternative cost functions for the sensitivity analysis. Overall, the degree of conjectural elasticities from newly developed empirical models tend to show more collusion state of market than those from traditional aggregated models. The conjectural elasticity from the distributional model and joint distribution model has closer value with conjectural elasticity from firm level data.

INTRODUCTION

As agricultural and food industries become increasingly integrated and concentrated, there have been numerous studies estimating the market power of these industries (e.g., Schroeter 1988; Azzam 1990, 1991; Chung and Tostao 2009, 2012). New empirical Industrial Organization (NEIO) models used in previous studies first derived conceptual models from profit-maximizing- theory of firm. The industry-level market power is represented by the market share weighted average of each firm's conjectural elasticity. Therefore, the estimation of firm-level conjectural elasticity is the first step to get market conduct parameter. However, available and affordable data are mainly aggregated, and it is difficult and expensive to obtain the firm-level data. The top four companies in the beef packing industry (CR4), which occupied 83% of commercial cattle slaughter in 2017, do not present their firms' data. Therefore, the market power parameter is usually estimated by aggregated data such as industry or market level data. The individual firm's behavior is difficult to estimate using aggregated data, and the interactions between the individual firms are also ignored in this situation. As a result, the market power parameter estimated using aggregated data can likely be overestimated or underestimated.

The empirical estimation of market power is usually based on aggregate time-series data at either market or industry level, which does not consider the heterogeneity of individual firm behavior (e.g., Schroeter 1988; Azzam 1990, 1991; Lopez, Azzam and Carmen 2002; Zheng and Vukina 2008; Ji, Chung and Lee 2017). In such studies, assuming homogeneous firms, the representative producer model ignores the diverse dispersion of each firm's market conduct parameter and assumes the same marginal cost and conjectural coefficient or elasticity. As a result, estimated market elasticities from some studies have insignificant or relatively small value (Schreoter 1998; Muth and Wohlgenant 1999; Morrison 2001).

It is well known in empirical econometrics that when relations are derived from microeconomic theory, but are estimated by means of aggregated data, the aggregation can lead to biased parameter estimates (Theil 1971; Maddala 1977; Stoker 1984, 1986, 1993). The applied econometrics literature indicates that ignoring heterogeneity in estimates of individual firm behavior (represented by conjectural coefficient or elasticity) may result in biased estimation of the overall market power of U.S. beef processors. Specifically, the most studies of market power are based on aggregated data, U.S. or state level (Table 1.1) data. Only a few studies' market power measurements are estimated with plant level data (Driscoll, Kambhampaty, and Purcell 1997; Morrison 2001; Crespi and Sexton 2005). As a result, the firm's heterogeneity is ignored and market power estimates are likely to be biased because unbiased estimation of market power highly depends on accurate estimation of marginal cost. This aggregation issue is highlighted in the literature of NEIO approach, for example, in Schroeter and Azzam (1990), Raper, Love and Shumway (2000), Morrison (2001).Standard errors of coefficients from aggregated data and individual firm-level data tend to be different , which can make different policy implication from statistical inference (Garrett 2003). . Therefore, the issue of aggregation bias raises concerns regarding the validity of market power estimated from aggregated data and highlights the need for research designed to enhance our understanding of aggregation bias in estimating market power.

OBJECTIVES

This study first discusses statistical processes to estimate the degree of aggregation bias and find which types of aggregation biases can likely happen. The aggregation bias consists of two components: the bias from covariance between variables and corresponding parameters and the bias caused by the use of improper aggregated data. If the covariance between variables and corresponding parameters is nonzero, which means all agents are heterogeneous, the covariance cannot be ignored. However, the "representative producer model" assumes all identical producers, which leads to the same conjectural elasticity and marginal cost for all producers. Therefore, this unreasonable assumption causes the aggregation bias. A typical method for making aggregate data is arithmetic mean, and this type of data is widely accepted to estimate econometric models. However, proper aggregate data for some equations, such as log equations, are not arithmetic mean but geometric mean. If researchers use arithmetic mean instead of geometric mean to aggregate log equations, then the estimated parameter should be biased.

Second, this study proposes new procedures to eliminate or at least reduce aggregation bias when estimating market power. Our first approach is to eliminate aggregation bias by using proper procedures for data aggregation. For example, the trans-log cost function includes the log value of each firm's production, and the logarithm of firm output can be transformed to a dispersion ratio by proper aggregation. Theil (1971) defines this procedure as an entropy measure of relative inequality. Similarly, trans-log consumer demand function has each individual's income term, and aggregated income has identical form of Theil's entropy measure (Berndt 1977; Deaton 1980a, 1980b; Lewbel 1992; Albuquerque 2003). Secondly, combining aggregate data and published firm-level data can reduce the aggregation bias. When one does not have firm-level data, but have only approximate information, such as average, variance, and distribution, she can combine the aggregate data with the additional information about the data. The third approach is a joint distribution approach with dummy variables. The individual marginal cost function has dummy variables indicating heterogeneity. The aggregation of dummy changed to proportion of corresponding firms respect to total firms (Stoker 1993).

The next section provides review of previous studies about aggregation bias. The methodology section shows the limitation of traditional conjectural elasticity based on data and introduces new approaches, hybrid models, to eliminate the aggregation bias. The data section discusses the data generation procedure of firm level data using the Monte Carlo technique. 360 monthly observation with one thousand firm level data are generated based on the true market power data. Then, estimation results from the macro model, aggregated model and hybrid model are discussed. The last section presents a brief summary of findings from our empirical models.

LITERATURE REVIEW

Appelbaum (1982) introduces a NEIO framework to estimate market power using a set of firm's input demand function and price-margin equation derived from a firm's profit function. This approach is applied to the U.S. beef packing industry to measure market power, and previous studies find statistically significant estimates of market power (Azzam and Pagoulatos 1990; Schreoter and Azzam 1990; Azzam 1992, Azzam and Park 1993, Koontz, Garcia, and Hudson 1993, Stiegert, Azzam, and Brorsen 1993). However, some of NEIO studies do not find evidence to support the existence of market power as Table 1 (Muth and Wohlgenant 1999; Schroeter, Azzam, and Zhang 2000; Paul 2001). Most previous studies of market power estimates are based on aggregate data, such as at the U.S. or state level, due to lack of available firm level data. The measurement of market power with aggregate data assumes that all firms are homogeneous. This assumption makes the biased estimation of marginal cost, and the market power estimates are biased or insignificant (Schroeter and Azzam 1990). The aggregate data issue is a serious cause of biased estimation in previous studies using NEIO, but to the best of our knowledge, this is the first work that shows how to reduce or eliminate the aggregation bias in estimating the NEIO models.

Many studies have shown that ignoring the heterogeneity causes biased estimators and introduced various methods to address the heterogeneity issue, particularly in estimating aggregated demand function (Theil 1971, Jorgensen, Lau and Stoker 1982, Stoker 1993, 2005). "Almost Ideal Demand System (AIDS)" uses an aggregated demand function with a distributional term, which is composed of entropy statistics (Deaton and Muellbauer 1980). Deaton and Muellbauer (1980) was extended to estimate aggregation bias in linear and quadratic AIDS (QUAIDS) models (Blundell et al 1993a, b; Mittelhammer, Shi and Wahl 1996; Denton and Mountain 2001, 2004; Matsuda 2006). The QUAIDS models were further extended to alternative functional forms such as log-linear and quadratic functions (Lewbel 1992; Garderen, Lee and Pesaran 2000; Albuquerque 2003; Moeltner 2003; Tenn 2006). Jorgensen, Lau and Stoker (1982) also extended Deaton and Muellbauer

(1980)'s study by incorporating dummy variables indicating categories of micro data values. These dummy variables can indicate various information of demographic distribution data, and this approach can reduce aggregation bias efficiently by addressing heterogeneity of micro agents. Denton and Mountain (2011, 2016) compare demand elasticities from micro data, aggregated level data, and aggregated data with the income distribution model. Our study extends Denton and Mountain (2011, 2016) by decomposing the aggregation biases mathematically to show causes of aggregation biases.

The usual panel estimation by the fixed or random effect model assumes that coefficients are homogeneous, and this assumption can cause the aggregation bias by ignoring the heterogeneity of coefficients. However, individual heterogeneity can be addressed using the random coefficient model (RCM) for panel analysis. Therefore, the aggregation bias can be found by comparing coefficients based on RCM with coefficients based on the fixed or random effect model. Nickell (1981) shows that panel analysis with the fixed or random effect model with aggregated data estimation are not consistent in a dynamic model or a time series model due to ignoring coefficient heterogeneity. Pesaran and Smith (1995), Biørn and Skjerpen (2004), Imbs, Mumtaz, Ravn, and Rey (2005) also estimated RCM to show inconsistency of estimates between micro and macro models.

METHODOLOGY

Traditional NEIO Estimation

Let's assume that each packer's output market is competitive, but raw material-input market is not competitive, in other words, an oligopsony market. The profit function of i^{th} packer is:

(1) $\pi_i = \{P - w(Y)\}y_i - C_i(y_i, v)$

where $Y = \sum_{i=1}^{n} y_i$,is industry level output , where y_i is raw material input and final output at firm-level by assuming the fixed proportion technology, P is output price, w is raw material input price, C_i is a function of processing cost, v is vector of input price except raw material input.

Equation (1) is written by profit maximization for firm i as:

(2) $P - w(Y) = w\varepsilon\theta_i + mc_i$

where $\varepsilon = \frac{\partial w}{\partial Y}\frac{Y}{w}$ is the inverse price elasticity of material input supply, $\theta_i = \frac{\partial Y}{\partial y_i}\frac{y_i}{Y}$ is the conjectural elasticity of i^{th} firm, $mc_i = \frac{\partial C_i}{\partial y_i}$ is marginal processing cost of i^{th} firm.

The i^{th} firm's trans-log cost function is given by:

$$(3) \quad \begin{aligned} \log c_i = {} & \beta_0 + \sum_{n=1}^{3}\beta_n \log w_n + \beta_y \log y_i + \frac{1}{2}\sum_{n=1}^{3}\sum_{m=1}^{3}\beta_{nm}\log w_n \log w_m + \sum_{n=1}^{3}\beta_{yn}\log y_i \log w_n \\ & + \beta_{yy}(\log y_i)^2 + \varepsilon_i \end{aligned}$$

where $\beta_{nm}=\beta_{mn}$, $n, m = K, L, M$, which means capital, labor and intermediate input, w_k, w_l, w_m are price of capital, labor and intermediate input.

Equation (2) with marginal cost function of equation (3) becomes the following equation

$$(4)\quad P - w = w\varepsilon\theta_i + \frac{c_i}{y_i}\left(\beta_{yi} + \beta_{yKi}\log w_{Ki} + \beta_{yLi}\log w_{Li} + \beta_{yMi}\log w_{Mi} + 2\beta_{yiyi}\log y_i\right)$$

The input demand function can be derived by Shephard's lemma, which means the derivative of the cost function of equation (3) with respect to the input price, w_K, w_L, w_M. The capital, labor and intermediate input demand functions are obtained as

$$(5)\quad s_{Ki} = \beta_K + \sum_{m=1}^{3}\beta_{Kmi}\log w_{Kmi} + \beta_{yKi}\log y_i\,,$$

$$s_{Li} = \beta_L + \sum_{m=1}^{3}\beta_{Lmi}\log w_{Lmi} + \beta_{yLi}\log y_i\,,$$

$$s_{Mi} = \beta_M + \sum_{m=1}^{3}\beta_{Mmi}\log w_{Mmi} + \beta_{yMi}\log y_i\,,$$

where $s_{Ki} = \frac{x_{Ki}w_{Ki}}{c_i}$, $s_{Li} = \frac{x_{Li}w_{Li}}{c_i}$, $s_M = \frac{x_{Mi}w_{Mi}}{c_i}$ and are capital, labor and intermediate cost-share equation, $c_i = w_{Ki}x_{Ki} + w_{Li}x_{Li} + w_{Mi}x_{Mi}$ is total cost of firm *i*.

The output demand function is given as

$$(6)\quad \ln y = a + \eta\ln(p/S) + \rho\ln(q/S)$$

where η is demand elasticity, ρ is income elasticity, q is GNP, and S is GNP deflator.

The i^{th} firm's conjectural elasticity can be estimated by the simultaneous equation model consisting of equation (4) and (5). The estimated conjectural elasticity means the packer's degree of oligopsony in the fed cattle market. If the $\theta_i = 0$, then the fed cattle market is a perfect competitive market. If the $\theta_i = 1$, then the fed cattle market is a monopsony market.

Aggregation Bias Issue in NEIO Models

The industry level marginal processing cost is the summation of each firm's marginal processing cost. However, packer (firm) level data for equation (4) are not available or difficult to obtain. Therefore, researchers usually estimate the conjectural elasticity with aggregated data, such as industry level data (Appelbaum 1982, Schroeter 1988, Azzam 1997). This approach has critical limitations that all packers have the same conjectural elasticity and also have identical marginal processing cost ($\bar{\theta} = \theta_i = \theta_j$, $mc = mc_i = mc_j$). The beef packing industry is capital intensive, and is one of the economy of scale industries. The top 5 (Tyson, JBS USA, Cargill, National, and American Foods Group) packers have 77.9% of total commercial cattle and hog slaughter in 2014. These major packers' production quantity is different with the rest of packers and their marginal costs are also different to small size packers. Therefore, the conjectural elasticity based on aggregated data is likely to be biased.

The industry level of equation (4) becomes the following equation under the assumption that all packers have identical conjectural elasticity and same marginal costs,

$$(7) \quad P - w = w\varepsilon\hat{\theta} + \frac{c}{y}\left\{\beta_y + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + \beta_{yy}\log Y\right\}$$

where $\hat{\theta}$ is industry level conjectural elasticity, W_K, W_L, and W_M is industry level data of capital, labor and intermediate input, Y is industry output,

The industrial conjectural elasticity is defined as the market share weighted average of firm's conjectural elasticity and is written by

$$(8) \quad \Theta = \sum_{i=1}^{n} s_i\theta_i$$

where Θ is industrial conjectural elasticity, s_i is market share of i^{th} firm, $s_i = y_i/Y$.

The conjectural elasticity of the industry level can be obtained by multiplying market share (s_i) to each firm's equation (4), and summing all firms, then the aggregated form of equation (4) is

$$(9)\quad P - w = w\varepsilon\Theta + \frac{1}{Y}\sum_{i=1}^{n} c_i \cdot \left(\beta_{yi} + \beta_{yKi}\log w_{Ki} + \beta_{yLi}\log w_{Li} + \beta_{yMi}\log w_{Mi} + 2\beta_{yiyi}\log y_i\right).$$

Equation (9) shows that margin (left side of equation 9) is the sum of the first term of right side of equation (9), which means market power, and the second term of right side of equation (9), which means marginal processing cost weighted by market share. The difference is clear by comparing equation (7) and (9). The variables in equation (7) are macro (industrial) level variables without proper aggregation processes. This equation system is considered as the macro model in this analysis, On the other hand, equation (9) is considered as the aggregated model.

The macro model assumes that each firm has identical conjectural elasticities and the same marginal costs as mentioned before. If we estimate equation (7) instead of (9), then the conjectural elasticity and parameter estimates will be biased. Equation (9) can be written by the following equation with relation to arithmetic, geometric means, and the covariance definition. The detailed derivation process is in appendix A.

$$(10)\qquad P - w = w\varepsilon\Theta + \frac{c}{y}\left\{\bar{\beta}_y + \bar{\beta}_{yK}\log\bar{w}_K + \bar{\beta}_{yL}\log\bar{w}_L + \bar{\beta}_{yM}\log\bar{w}_M + \bar{\beta}_{yy}\log\bar{y}\right\}$$

$$+\frac{c}{y}\left\{\frac{w\varepsilon}{\bar{c}}\operatorname{cov}(y_i,\theta_i) + \operatorname{cov}(\beta_{yKi},\log w_{Ki}) + \operatorname{cov}(\beta_{yLi},\log w_{Li}) + \operatorname{cov}(\beta_{yMi},\log w_{Mi}) + \operatorname{cov}(\beta_{yiyi},\log y_i)\right\}$$

$$+\frac{n}{y}\left\{\operatorname{cov}(c_i,\beta_{yi}) + \operatorname{cov}(c_i,\beta_{yKi}\log w_{Ki}) + \operatorname{cov}(c_i,\beta_{yLi}\log w_{Li}) + \operatorname{cov}(c_i,\beta_{yMi}\log w_{Mi}) + \operatorname{cov}(c_i,\beta_{yiyi}\log y_i)\right\}$$

$$-\frac{\bar{c}}{2y}\left\{\bar{\beta}_{yK}\sum_{i=1}^{n}\left(\log w_{Ki} - \log\bar{w}_K^g\right)^2 + \bar{\beta}_{yL}\sum_{i=1}^{n}\left(\log w_{Li} - \log\bar{w}_L^g\right)^2 + \bar{\beta}_{yM}\sum_{i=1}^{n}\left(\log w_{Mi} - \log\bar{w}_M^g\right)^2 + \bar{\beta}_{yy}\sum_{i=1}^{n}\left(\log y_i - \log\bar{y}^g\right)^2\right\}$$

where $\bar{w}_K^g$, $\bar{w}_L^g$ and $\bar{w}_M^g$ is geometric mean of w_{Ki}, w_{Li}, and w_{Mi}.

Equation (10) is the properly aggregated model and shows the difference, especially the covariance terms and square term, with the macro equation (7).

If researchers estimate the macro model instead of the aggregated model, the estimated parameters will be biased due to specification error. If the covariance terms and second order approximation terms of equation (9) are zero, the aggregation bias will vanish. Theil (1971) showed that covariance terms are generated by the heterogeneity of individual firms. If the firms have homogeneous marginal cost and input demand quantity, then the aggregation bias formed by cross section heterogeneity will vanish. The difference between arithmetic mean and geometric mean generates the last line of equation (10). If w_{Ki}, w_{Li}, w_{Mi} and y_i, have the same value across the cross section, then the arithmetic mean and geometric mean are identical and these second order approximation terms in the last line will disappear. If all of the firm's data are identical across the cross section, then the aggregated model equation (10) will be the same with the macro model equation (7). However, this assumption cannot be accepted in the real world. Each firm has different technologies, capital, and marketing conditions. In addition, most aggregated data are not generated by geometric mean, but by arithmetic means of micro variables. And geometric mean has different values with arithmetic means unless all valuables are identical. So if researchers estimate equation (7) instead of equation (10), then the omitted terms will be submerged to error term and make biased parameters.

Equation (10) is written as the following equation to show matrix form.

$$(11) \qquad Y = \overline{X}\overline{\beta} + \xi$$

where $Y = \dfrac{(P-w)y}{n\overline{c}}$, $\xi = \dfrac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(\beta_i - \overline{\beta}\right) + \dfrac{1}{\overline{c}n}\sum_{i=1}^{n}\left\{\left(X_i - X^c\right)B_i - \left(\overline{X} - X^c\right)\overline{B}\right\}\left(C_i - \overline{C}\right) - \dfrac{1}{n}\sum_{i=1}^{n}S_{x,ig}^2\overline{\beta} + \varepsilon$,

$$\bar{X} = \begin{bmatrix} 1 & \frac{\varepsilon w}{\bar{c}}\bar{y}_1 & \log \bar{w}_{K1} & \log \bar{w}_{L1} & \log \bar{w}_{M1} & \log \bar{y}_1 \\ 1 & \frac{\varepsilon w}{\bar{c}}\bar{y}_2 & \log \bar{w}_{K2} & \log \bar{w}_{L2} & \log \bar{w}_{M2} & \log \bar{y}_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \frac{\varepsilon w}{\bar{c}}\bar{y}_t & \log \bar{w}_{Kt} & \log \bar{w}_{Lt} & \log \bar{w}_{Mt} & \log \bar{y}_t \end{bmatrix} \quad X_i = \begin{bmatrix} 1 & \frac{\varepsilon w}{\bar{c}} y_{i1} & \log w_{Ki1} & \log w_{Li1} & \log w_{Mi1} & \log y_{i1} \\ 1 & \frac{\varepsilon w}{\bar{c}} y_{i2} & \log w_{Ki2} & \log w_{Li2} & \log w_{Mi2} & \log y_{i2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \frac{\varepsilon w}{\bar{c}} y_{it} & \log w_{Kit} & \log w_{Lit} & \log w_{Mit} & \log y_{it} \end{bmatrix}$$

$$X^c = \begin{bmatrix} 0 & \frac{\varepsilon w}{\bar{c}} y_{i1} & 0 & 0 & 0 & 0 \\ 0 & \frac{\varepsilon w}{\bar{c}} y_{i2} & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \frac{\varepsilon w}{\bar{c}} y_{it} & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \bar{\beta} = \begin{bmatrix} \bar{\beta}_y \\ \bar{\theta} \\ \bar{\beta}_{yK} \\ \bar{\beta}_{yL} \\ \bar{\beta}_{yM} \\ \bar{\beta}_{yy} \end{bmatrix} \quad \beta_i = \begin{bmatrix} \beta_{yi} \\ \theta_i \\ \beta_{yKi} \\ \beta_{yLi} \\ \beta_{yMi} \\ \beta_{yiyi} \end{bmatrix} \quad \bar{C} = \begin{bmatrix} \bar{c} \\ \bar{c} \\ \bar{c} \\ \bar{c} \\ \bar{c} \\ \bar{c} \end{bmatrix}, \quad C_i = \begin{bmatrix} c_i \\ c_i \\ c_i \\ c_i \\ c_i \\ c_i \end{bmatrix},$$

$$\bar{B} = \begin{bmatrix} \bar{\beta}_y & 0 & 0 & 0 & 0 & 0 \\ 0 & \bar{\theta} & 0 & 0 & 0 & 0 \\ 0 & 0 & \bar{\beta}_{yK} & 0 & 0 & 0 \\ 0 & 0 & 0 & \bar{\beta}_{yL} & 0 & 0 \\ 0 & 0 & 0 & 0 & \bar{\beta}_{yM} & 0 \\ 0 & 0 & 0 & 0 & 0 & \bar{\beta}_{yy} \end{bmatrix} \quad B_i = \begin{bmatrix} \beta_{yi} & 0 & 0 & 0 & 0 & 0 \\ 0 & \theta_i & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta_{yKi} & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_{yLi} & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta_{yMi} & 0 \\ 0 & 0 & 0 & 0 & 0 & \beta_{yiyi} \end{bmatrix}$$

$$S^2_{x,ig} = \begin{bmatrix} 0 & 0 & (\log w_{Ki1} - \log \bar{w}^g_{K1})^2 & (\log w_{Li1} - \log \bar{w}^g_{L1})^2 & (\log w_{Mi1} - \log \bar{w}^g_{M1})^2 & (\log y_{i1} - \log \bar{y}^g_1)^2 \\ 0 & 0 & (\log w_{Ki2} - \log \bar{w}^g_{K2})^2 & (\log w_{Li2} - \log \bar{w}^g_{L2})^2 & (\log w_{Mi2} - \log \bar{w}^g_{M2})^2 & (\log y_{i2} - \log \bar{y}^g_2)^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & (\log w_{Kit} - \log \bar{w}^g_{Kt})^2 & (\log w_{Lit} - \log \bar{w}^g_{Lt})^2 & (\log w_{Mit} - \log \bar{w}^g_{Mt})^2 & (\log y_{it} - \log \bar{y}^g_t)^2 \end{bmatrix}.$$

The error term (ξ) of equation (11) consists of covariance and square term of approximation and these properties do not meet the basic assumption that the mean of error term is zero. This non zero mean of error term is generated by aggregation bias, and this bias can be drawn as the following equation. The detailed derivation process is in appendix B.

(12) $$\bar{b} = (\bar{X}'\bar{X})^{-1}\bar{X}'Y = (\bar{X}'\bar{X})^{-1}\bar{X}'(\bar{X}\bar{\beta} + \xi) = (\bar{X}'\bar{X})^{-1}\bar{X}'\bar{X}\bar{\beta} + (\bar{X}'\bar{X})^{-1}\bar{X}'\xi$$

$$= \overline{\beta} + \frac{1}{n}\sum_{i=1}^{n}\left\{\left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'X_i - I\right\}\beta_i + \frac{1}{\overline{c}n}\sum_{i=1}^{n}\left\{\left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\left(X_i - X^c\right)B_i\left(C_i - \overline{C}\right)\right\}$$

$$-\frac{1}{n}\left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\sum_{i=1}^{n}S_{x,ig}^2\overline{\beta} + \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\varepsilon .$$

Expectation value of equation (12) is

$$(13) \qquad E(b) = \overline{\beta} + \sum_{i=1}^{n}\left\{HP_i - \frac{1}{n}I\right\}\beta_i + \frac{1}{\overline{c}n}\sum_{i=1}^{n}HC_iB_i\left(C_i - \overline{C}\right) - \frac{1}{n}\sum_{i=1}^{n}R_i$$

where $HP_i = \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\frac{1}{n}X_i, HC_i = \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\left(X_i - X^c\right), R_i = \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'S_{x,ig}^2\overline{\beta}$.

The second term on the right side of equation (13) is aggregation bias due to ignoring the parameter heterogeneity, the third term is aggregation bias originated from ignoring individual firm's cost, and the last term is the aggregation bias produced by using linearly aggregated data for the nonlinear macro model. If the parameter of each firm is identical, then the second term will disappear, and if each firm's cost is the same, then the third term also will vanish. These components of aggregation bias can be estimated by the following process.

Equation (13) can be changed to scalar form and the conjectural elasticity term as

$$(14) \qquad E(\Theta) = \overline{\theta} + \sum_{i=1}^{n}\left(hp_{11i} - \frac{1}{n}\right)\theta_i + \sum_{i=1}^{n}\left(hp_{12i}\beta_{yKi}\right) + \sum_{i=1}^{n}\left(hp_{13i}\beta_{yLi}\right) + \sum_{i=1}^{n}\left(hp_{14i}\beta_{yMi}\right) + \sum_{i=1}^{n}\left(hp_{15i}\beta_{yiyi}\right)$$

$$+\frac{1}{\overline{c}n}\left\{\sum_{i=1}^{n}\left(c_i - \overline{c}\right)\left(hc_{10i}\beta_{yi} + hc_{11i}\,\theta_i + hc_{12i}\beta_{yKi} + hc_{13i}\beta_{yLi} + hc_{14i}\beta_{yMi} + hc_{15i}\beta_{yiyi}\right)\right\} - \frac{1}{n}\sum_{i=1}^{n}r_{1i}$$

The first term on the right side of equation (14) is the mean of conjectural elasticity, and the second term is derived from the heterogeneity of each firm's conjectural elasticity. The other terms including hp_{nmi} on the first line are aggregation bias due to heterogeneity of each micro parameter, and the term including hc_{nmi} in parenthesis on the second line is formed by aggregation bias by ignoring the heterogeneity of each firm's cost. The last term r_{1i}, is aggregation bias generated by improper data aggregation (arithmetic means instead of geometric means). The elements of matrixes HP_i and HC_i can be derived from the definition of each matrix and the elements can be estimated as auxiliary following equations. The other auxiliary equations are in appendix C.

$$(15) \qquad \frac{1}{n}\frac{\varepsilon w}{\bar{c}} y_{it} = hp_{01i} + hp_{11i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hp_{21i}\log \overline{w}_{Kt} + hp_{31i}\log \overline{w}_{Lt} + hp_{41i}\log \overline{w}_{Mt} + hp_{51i}\log \bar{y}_t$$

Elimination of Aggregation Bias

The aggregation biases are generated when the macro data model was estimated without proper data aggregation process. So the best approach to avoid aggregation bias is estimation using micro level data only. However, it is difficult to obtain the whole micro level data for estimation as mentioned before, and in this case, researchers need to replace absent micro level data with available aggregated data. There are several methods to reduce the aggregation bias by incorporating micro data into the macro model and these models are considered as hybrid models. For this approach, we need at least one kind of micro (firm) level data to insert in the macro model and assume that beef packers have not presented their input cost, such as capital, labor and intermediate input cost data, but showed their beef production data or production capacity. The hybrid models are distributional approach with specific micro data, distributional approach without specific data, and joint distribution approach with dummy variables. In addition, other cost function forms, Generalized Leontief and Quadratic cost function, are analyzed for sensitivity analysis.

A. Distributional Approach with Firm's Production Data

Berndt, Darrough and Diewart (1977) introduced direct methods of distributional information into aggregated trans-log demands equations. Deaton and Muellbauer's (1980a, 1980b) showed this approach in their popular "Almost Ideal Demand System" or AIDS to aggregate each individual's budget share.

Let's assume that researchers have firm level beef production data and macro data of marginal processing costs, which means $y_i \neq y_j$, $w_{xi} = w_{xj}$ for *x* = *K*, *L*, *M*, $i \neq j$. Then equation (4) can be changed as

$$(16) \qquad y_i\theta_i = \frac{(P-w)y_i}{w\varepsilon} - \frac{c}{w\varepsilon}\left(\beta_{yi} + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + 2\beta_{yiyi}\log y_i\right)$$

The conjectural elasticity of industry level (Θ) is written as

$$(17) \qquad \Theta = \sum_{i=1}^{n} s_i\theta_i = \sum_{i=1}^{n}\frac{y_i}{y}\theta_i = \frac{1}{y}\sum_{i=1}^{n} y_i\theta_i = \left(\sum_{i=1}^{n} y_i\theta_i \Big/ n\right)\Bigg/\left(\sum_{i=1}^{n} y_i \Big/ n\right) = \frac{E(y\theta)}{\bar{y}}$$

Equation (17) is written as

$$(18) \qquad \Theta = \frac{1}{\bar{y}}\int_L^U \left\{\frac{(P-w)y_i}{w\varepsilon} - \frac{c_i}{w\varepsilon}\left(\beta_{yi} + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + 2\beta_{yiyi}\log y_i\right)\right\}\phi(y)\,dy$$

where $\phi(y)$ is density function of *y*.

Equation (18) can be simplified as

$$(19) \qquad P - w = w\varepsilon\Theta + \frac{c}{\bar{y}}\left\{\beta_{yi} + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + 2\beta_{yiyi}E(\log y_i)\right\}$$

The last term of equation (19) in parenthesis, $E(\log y_i)$ can be changed as

(20) $$E(\log y_i) = \frac{1}{n}\sum_{i=1}^{n}\log y_i = \log\prod_{i=1}^{n} y_i^{\frac{1}{n}} = \log \bar{y}^{g}$$

As we set all firms share same aggregated data, this means that all firm's marginal input cost is the same. So the covariance term of equation (l0) has vanished and geometric mean and arithmetic means have the same value for the same reason. As a result, equation (19) is a hybrid form between equation (7) and (10).

B. Distribution Approach without Specific Production Information

In this paper, we have generated production data of each firm and can get the average of production, E(y_i). However, firm level data are usually unavailable, and each firm's specific production data is more difficult to obtain. In this case, we can get an average value of production approximately based on presented production distribution. Let's suppose that we only have the partial information about each firm's production data based on previous research and presented data. Then we assume that the production of each firm is Gamma distribution as $y_i \sim \Gamma(\alpha, 1/\beta)$, then the price-margin equation contains the marginal cost function of trans-log form, so equation (19) is changed as

(21) $$P - w = w\varepsilon\Theta + \frac{c\beta}{\alpha}\left\{\beta_{yi} + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + 2\beta_{yy}\left(\psi(k) + \ln(\theta)\right)\right\}$$

where $\bar{y}_t = \alpha/\beta$, $E(\log y_{it}) = \psi(\alpha) + \ln(\beta)$, $\psi(k)$ is digamma function.

C. Joint Distributional Approach

Equation (4), each firm's price equation with dummy variables can be written as

(22) $$P - w = w\varepsilon\theta_i + \frac{c}{y_i}\left\{\beta_{yi} + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + 2\beta_{yiyi}\log y_i + \sum_s^S \beta_{As}A_{si}\right\}$$

where A_{si} is a dummy variable indicating production quantity categories of firm *i*, *s*=1,2,…,*S*, β_{As} is the parameter of each dummy variable.

Equation (22) can be aggregated the same way as equation (19) as

(23) $$P - w = w\varepsilon\Theta + \frac{c}{\bar{y}}\left\{\beta_{yi} + \beta_{yK}\log W_K + \beta_{yL}\log W_L + \beta_{yM}\log W_M + 2\beta_{yy}E\left(\log y\right) + \frac{1}{n}\sum_s^S \beta_{As}R_s\right\}$$

where $R_s = \sum_{i=1}^{n} y_i A_{si}$

The last term of equation (23) can be simplified as

(24) $$\frac{1}{\bar{y}\cdot n}\sum_{i=1}^{n} y_i A_{si} = \frac{\frac{1}{n}\sum_{i=1}^{n} y_i A_{si}}{\bar{y}} = \sum_{i=1}^{n} y_i A_{si} \Big/ \sum_{i=1}^{n} y_i$$

The above equation (24) is a proportion of total production accounted for by firms with A_{st}=l. So equation (23) has a size distribution of production of each firm E(log y_i) and heterogeneity effect of the production proportion of the firms.

D. Application to Another Cost Function Form

The Trans-log cost function is estimated for the conjectural elasticity as mentioned above. However, many previous studies point out that functional forms affect the estimation of conjectural elasticity (Azzam and Pagoulatos, 1991; Sexton, 2000). The other form of cost function is considered for a sensitivity analysis of conjectural elasticity estimation. The included cost function forms are Generalized Leontief and Quadratic functions.

D-1. Generalized Leontief Cost Function

The Generalized Leontief cost function form is

$$(25)\qquad c = y_i \sum_n \sum_m \beta_{nm} \left(w_n w_m \right)^{\frac{1}{2}} + y_i^2 \sum_n \beta_n w_n$$

where *n, m*=*K*, *L* and *M*.

Equation (2) with marginal cost function of equation (25) is written as

$$(26)\qquad P - w = w\varepsilon\theta_i + \beta_{KKi} w_{Ki} + \beta_{LLi} w_{Li} + \beta_{MMi} w_{Mi} + 2y_i \left(\beta_{Ki} w_{Ki} + \beta_{Li} w_{Li} + \beta_{Mi} w_{Mi} \right)$$
$$+ 2\beta_{KLi} \left(w_{Ki} w_{Li} \right)^{\frac{1}{2}} + 2\beta_{KMi} \left(w_{Ki} w_{Mi} \right)^{\frac{1}{2}} + 2\beta_{LMi} \left(w_{Li} w_{Mi} \right)^{\frac{1}{2}}$$

The assumption that $w_{xi} = w_{xj}$ *for* $x = K, L, M$, $i \neq j$ and beef production data of each firms, y_i is micro level data, then the aggregated form of equation (26) by distributional approach is

$$(27)\qquad P - w = w\varepsilon\Theta + 2y \cdot HHI \cdot \left(\beta_K w_K + \beta_L w_L + \beta_M w_M \right) + \beta_{KK} w_K + \beta_{LL} w_L + \beta_{MM} w_M$$
$$+ 2\beta_{KL} \left(w_K w_L \right)^{\frac{1}{2}} + 2\beta_{KM} \left(w_K w_M \right)^{\frac{1}{2}} + 2\beta_{LM} \left(w_L w_M \right)^{\frac{1}{2}}$$

where *HHI* means the Herfindahl-Hirschman indices, $HHI = \sum_{i=1}^{n} \left(\frac{y_i}{Y} \right)^2$.

The HHI can be changed following the equation if we do not know the exact value of HHI, but we have only distribution of y_i. If the production of each firm is Gamma distribution as, $y_{it} \sim \Gamma(\alpha, 1/\beta)$, then the price-margin equation contains marginal cost function of trans-log form, equation (27) is as

$$(28) \qquad P - w = w\varepsilon\Theta + 2y \cdot \frac{\alpha+1}{n\alpha}\left(\beta_K w_K + \beta_L w_L + \beta_M w_M\right) + \beta_{KK} w_K + \beta_{LL} w_L + \beta_{MM} w_M$$

$$+ 2\beta_{KL}\left(w_K w_L\right)^{\frac{1}{2}} + 2\beta_{KM}\left(w_K w_M\right)^{\frac{1}{2}} + 2\beta_{LM}\left(w_L w_M\right)^{\frac{1}{2}}$$

where *n* is the observation number.

The aggregated form of equation (26) by joint distributional with dummy variable approach is

$$(29) \qquad P - w = w\varepsilon\Theta + 2y \cdot HHI \cdot \left(\beta_K w_K + \beta_L w_L + \beta_M w_M\right) + \beta_{KK} w_K + \beta_{LL} w_L + \beta_{MM} w_M$$

$$+2\beta_{KL}\left(w_K w_L\right)^{\frac{1}{2}} + 2\beta_{KM}\left(w_K w_M\right)^{\frac{1}{2}} + 2\beta_{LM}\left(w_L w_M\right)^{\frac{1}{2}} + \sum_{s}^{S} \beta_{AS} \left(\sum_{i=1}^{n} y_i A_{Si} \Big/ \sum_{i=1}^{n} y_i \right)$$

D-2 Normalized Quadratic Cost Function

The normalized quadratic cost function form is

$$(30) \qquad c = \sum_n \beta_n w_n + \beta_y y + \frac{1}{2}\left(\sum_n \sum_m \beta_{nm} w_n w_m + \beta_{yy} y^2 \right) + \sum_n \beta_{ny} w_n y$$

where $n, m = K, L, M$.

Equation (2) with marginal cost function of equation (30) is written as

$$(31) \qquad P - w = w\varepsilon\theta_i + \beta_{yi} + \beta_{yyi} y_i + \beta_{Kyi} w_{Ki} + \beta_{Lyi} w_{Li} + \beta_{Myi} w_{Mi}$$

If we assume that $w_{ni} = w_{nj}$ *for* $n = K, L, M$, $i \neq j$ and beef production data of each firms, y_i is firm level data, then the aggregated form of equation (31) by distributional approach is

$$P - w = w\varepsilon\Theta + \beta_y + \beta_{yy} y \cdot HHI + \beta_{Ky} w_K + \beta_{Ly} w_L + \beta_{My} w_M \tag{32}$$

The expectation value of y_t, $\bar{y}_t = \alpha/\beta$, $E(\log y_{it}) = \psi(\alpha) + \ln(\beta)$, $\psi(k)$ is digamma function when production of each firm is Gamma distribution as, $y_{it} \sim \Gamma(\alpha, 1/\beta)$. Then equation (32) is changed to

$$P - w = w\varepsilon\Theta + \beta_y + \beta_{yy} y \cdot \frac{\alpha + 1}{n\alpha} + \beta_{Ky} w_K + \beta_{Ly} w_L + \beta_{My} w_M \ . \tag{33}$$

The aggregated equation with joint distributional with dummy variable approach is

$$P - w = w\varepsilon\Theta + \beta_y + \beta_{yy} y \cdot HHI + \beta_{Ky} w_K + \beta_{Ly} w_L + \beta_{My} w_M + \sum \beta_{AS} \left(\sum_{i=1}^{n} y_i A_{Si} \Big/ \sum_{i=1}^{n} y_i \right) \tag{34}$$

DATA

The data sets were collected from the Economic Research Service (ERS) of the United States Department of Agriculture (USDA/ERS), Grain Inspection, Packer and Stockyards Administration (USDA/GIPSA), and the National Agricultural Statistics Service (USDA/NASS). Steer and heifer slaughter quantity is used proxy of beef production from Livestock Slaughter Annual Summary of National Agricultural Statistics Service, United States Department of Agriculture (USDA). Cattle slaughter quantity is from NASS of USDA, Capital, labor and material input price of the beef packing industry is from Industry Productivity and Costs Database of Bureau of Labor Statistics (BLS), United States Department of Labor (USDL). Beef price is from the ERS of the USDA and income is Per Capita GDP. Retail output is total U.S. commercial beef production from *red meat year book* of ERS, USDA. The retail sales data is from *progressive Grocer magazine*, beef retail price is from ERS, USDA. The detailed statistics of data are presented in Table 1-2.

Some firm' slaughter and capacity data are obtained from Cattle Buyers Weekly (CBW). However, the other firm level data are rarely available in the real world; therefore, the Monte Carlo technique is used to generate the firm level data. One thousand firm level data with 360 monthly observations (from January 1980 to December 2009) are generated based on the true market power parameter. The data generating process is as follows. First, the theoretical model is derived from processor's profit maximization equation. Second, the parameters of each equation from (5) to (9) are estimated using the collected data set. Then the estimated parameter is used as a starting value and the variance-covariance matrix is obtained. These estimated parameters and variance–covariance matrix analyzed in this process are given in the Appendix D. Third, Cholesky decomposition is applied variance-covariance matrix to obtain random error. Fourth, generated multivariate error terms are added to each equation for stochastic simulation of endogenous variables. Finally, each firm level data are generated by a known market power parameter.

RESULTS

The estimation system has five simultaneous equations (s_K , s_L , s_M , log y_i, price-margin equation) and are estimated using the General Moment Methods (GMM) procedure. The instrumental variables approach is used due to endogeneity of some variables. The instrumental variables are HHI for cattle slaughter, CR4, steer and heifer price and quantity of Nevada, Texas, cattle on feed, cattle placement, cattle on marketing, pork and chicken price, and income. The price elasticity of raw material input is assumed at 0.45 (Brester and Wohlgenant 1993) for simplicity.

Table 1.3 shows the estimation results of conjectural elasticity based on firm level data, *E(Θ)*, simple average value of each firm's conjectural elasticity and aggregation bias. The simple average value of each firm's conjectural elasticity is 0.1461 and aggregation bias is -0.0096. The aggregation bias consists of three terms originated from the heterogeneity of parameters, heterogeneity of cost, and linearly aggregated data for the nonlinear aggregated model. The aggregation bias from the heterogeneity of parameters is 0.0668 and from heterogeneity of cost is 0.0043. The aggregation bias due to linearly aggregated data for the nonlinear aggregated model is -0.0807 and shows the largest absolute value of bias. Sum of aggregation bias, -0.0096, looks to be a small value, however, its absolute value is not a small value compared to the average of micro conjectural elasticity. Therefore, if the proper aggregation methods are not considered, the estimation results are likely to be biased.

Table 1.4 presents the estimation result of each model. The conjectural elasticity based on firm level data (Θ) with trans-log cost function form is 0.1712, and the conjectural elasticity based on aggregated data ($\hat{\theta}$) is 0.1464 and is significant at 1% level. The conjectural elasticity from aggregated data shows less value than the conjectural elasticity (Θ) from firm level data. All conjectural elasticities from the distribution models are larger values than the conjectural elasticity from aggregated model ($\hat{\theta}$). Specifically, conjectural elasticity of entropy approach and

Gamma distribution model is 0.1548, 0.1595 and is significant at 1% level. Conjectural elasticity of joint distribution approach is 0.1492. The conjectural elasticity from aggregated data shows less value than the conjectural elasticity of firm level data, and this means that conjectural elasticity from aggregated level is likely to underestimate the conjectural elasticity and is biased estimate can supply policy maker's with improper implications. However, the conjectural elasticity from distribution approach shows a closer value to the conjectural elasticity of firm level data because the aggregation bias is controlled in the model. The other parameter estimates of each model is suggested at Table 1.5.

The conjectural elasticity based on firm level data (Θ) with generalized Leontief form is 0.1536, and the conjectural elasticity based on aggregated data ($\hat{\theta}$) is 0.1099 in Table 1.4. The conjectural elasticity from aggregated data also shows less value than conjectural elasticity (Θ) from firm level data as trans-log cost function approach. The conjectural elasticity of entropy approach and Gamma distribution model is 0.1008 and 0.1147, and the conjectural elasticity of joint distribution approach is 0.1119. The conjectural elasticity of Gamma distribution and joint distribution approach show larger value than the aggregated model. The conjectural elasticity from aggregated data shows less value than conjectural elasticity of firm level data as seen in the previous case. The other parameter estimates of each model is suggested at Table 1.6.

The conjectural elasticity based on firm level data (Θ) with normalized quadratic form is 0.1679, and the conjectural elasticity based on aggregated data ($\hat{\theta}$) is 0.0633 in Table 1.4. The conjectural elasticity from aggregated data also shows less value than the conjectural elasticity (Θ) from firm level data as seen in previous approaches. The conjectural elasticity of entropy approach and log normal distribution model is 0.0656 and 0.0656, and the conjectural elasticity of joint distribution approach as 0.0658. The conjectural elasticities from distributional approach and joint distribution approach exist between aggregated model and firm level model. The other parameter estimates of each model is suggested at Table 1.7.

CONCLUSIONS

The conjectural elasticity is usually estimated using aggregated level data due to the lack of data availability, and therefore, conjectural elasticity of industrial level is estimated under assumptions that all firms have the same conjectural elasticity and identical marginal cost. In this case, the conjectural elasticity estimates are typically biased by ignoring heterogeneity of individual firms.

This paper demonstrates how one can improve the conjectural elasticity estimation using proper aggregation processes. First, we showed mathematically that the estimation results from aggregated data were not identical to those from firm level data unless all firms have identical (homogeneous) cost function, market share, and conjectural elasticity. Then we derived a few approaches that can reduce the aggregation bias by incorporating public micro level data in the empirical model.

To show validation of our distribution model, the firm level data is generated using Monte Carlo techniques and obtain each firm's conjectural elasticity. The distribution model and joint distribution model are introduced to reduce aggregation bias for estimation conjectural elasticity. The distribution approach incorporates the public micro data term into the aggregated model, and this term has the distribution information.

The joint distribution model has dummy variables indicating the category of the micro data, and this term can have distribution information by aggregation process. In addition, the conjectural elasticity can be different based on the cost function type. We test three different types of cost function (Trans-log, Generalized Leontief and Quadratic cost function). The results show that conjectural elasticity based on firm level data shows different values with conjectural elasticity based on firm level data, and so do other types of cost functions. The conjectural elasticity from the distribution model and joint distribution model show closer value with conjectural elasticity from firm level data.

The data availability is an important issue to researchers. The conjectural elasticity based on firm level data explain the degree of market power. However, the micro level data is not available and difficult to obtain. In this case, the distribution model shows better conjectural elasticity estimates than aggregated level data analysis alone.

The limitation of this study is availability of firm level data. The distribution model can improve the estimation of conjectural elasticity but still needs small portions of firm level data to estimate distribution model or joint distribution model.

REFERENCES

Albuquerque, P. H. (2003). A practical log-linear aggregation method with examples: heterogeneous income growth in the USA. *Journal of Applied Econometrics, 18(6)*, 665-678. doi:10.1002/jae.715

Appelbaum, E. (1982). The estimation of the degree of oligopoly power. *Journal of Econometrics*, 19(2-3), 287-299.

Azzam, A., & Park, T. (1993). Testing for switching market conduct. *Applied Economics*, 25(6), 795-800.

Azzam, A. M. (1992). Testing the competitiveness of food price spreads. *Journal of Agricultural Economics*, 43(2), 248-256.

Azzam, A. M. (1997). Measuring market power and cost-efficiency effects of industrial concentration. *The Journal of Industrial Economics*, 45(4), 377-386.

Azzam, A. M., & Pagoulatos, E. (1990). Testing oligopolistic and oligopsonistic behaviour: an application to the us meat-packing industry. *Journal of Agricultural Economics*, 41(3), 362-370.

Azzam, A. M., & Schroeter, J. R. (1991). Implications of increased regional concentration and oligopsonistic coordination in the beef packing industry. Western *Journal of Agricultural Economics*, 374-381.

Azzam, A. M., & Schroeter Jr, J. R. (1995). The tradeoff between oligopsony power and cost efficiency in horizontal consolidation: An example from beef packing. *American Journal of Agricultural Economics*, 77(4), 825-836.

Berndt, E. R., Darrough, M. N., & Diewert, W. E. (1977). Flexible functional forms and expenditure distributions: An application to Canadian consumer demand functions. *International Economic Review*, 651-675.

Biørn, E., & Skjerpen, T. (2004). Aggregation biases in production functions: a panel data analysis of Translog models. *Research in Economics*, 58(1), 31-57.

Blundell, R., Meghir, C., & Weber, G. (1993). Aggregation and consumer behaviour: some recent results. *Ricerche Economiche*, 47(3), 235-252.

Blundell, R., Pashardes, P., & Weber, G. (1993). What do we learn about consumer demand patterns from micro data? *The American economic review*, 570-597.

Blundell, R., & Stoker, T. M. (2005). Heterogeneity and aggregation. *Journal of Economic literature*, 43(2), 347-391.

Bresnahan, T. F. (1989). Empirical studies of industries with market power. *Handbook of industrial organization*, 2, 1011-1057.

Brester, G. W., & Wohlgenant, M. K. (1993). Correcting for measurement error in food demand estimation. *The Review of Economics and Statistics*, 352-356.

Chakrabarty, M., Schmalenbach, A., & Racine, J. (2006). On the distributional effects of income in an aggregate consumption relation. *Canadian Journal of Economics/Revue canadienne d'économique*, 39(4), 1221-1243.

Chang, B.-H., Lipsitz, S., & Waternaux, C. (2000). Logistic regression in meta-analysis using aggregate data. *Journal of Applied Statistics*, 27(4), 411-424.doi:10.1080/02664760050003605

Chung, C., & Kaiser, H. M. (2002). Advertising evaluation and cross-sectional data aggregation. *American Journal of Agricultural Economics*, 84(3), 800-806.

Chung, C., & Tostão, E. (2009). Nonparametric Estimation of Oligopsony Power in First-Price Auction. *Journal of Agricultural Economics*, 60(2), 318-333.

Crespi, J. M., & Sexton, R. J. (2005). A Multinomial logit framework to estimate bid shading in procurement auctions: Application to cattle sales in the Texas Panhandle. *Review of Industrial Organization*, 27(3), 253-278.

Crespi, J. M., Xia, T., & Jones, R. (2010). Market power and the cattle cycle. *American Journal of Agricultural Economics*, 92(3), 685-697.

Cattle Buyer Weekly, Marketing and Business News for the Beef Industry. Internet site: https://cattlebuyerweekly.com

Deaton, A., & Muellbauer, J. (1980a). An almost ideal demand system. *The American economic review*, 70(3), 312-326.

Deaton, A., & Muellbauer, J. (1980b). *Economics and consumer behavior*: Cambridge university press.

Denton, F. T., & Mountain, D. C. (2001). Income distribution and aggregation/disaggregation biases in the measurement of consumer demand elasticities. *Economics Letters*, 73(1), 21-28.

Denton, F. T., & Mountain, D. C. (2004). Aggregation effects on price and expenditure elasticities in a quadratic almost ideal demand system. *Canadian Journal of Economics/Revue canadienne d'économique*, 37(3), 613-628.

Denton, F. T., & Mountain, D. C. (2011). *Aggregation and other biases in the calculation of consumer elasticities for models of arbitrary rank* (No. 447). QSEP Research Report, McMaster University.

Denton, F. T., & Mountain, D. C. (2011b). Exploring the effects of aggregation error in the estimation of consumer demand elasticities. *Economic Modelling*, 28(4), 1747-1755.

Denton, F. T., & Mountain, D. C. (2013). The implications of mean scaling for the calculation of aggregate consumer elasticities. *The Journal of Economic Inequality*, 12(3), 297-314. doi:10.1007/s10888-013-9256-5

Driscoll, P. J., Kambhampaty, S. M., & Purcell, W. D. (1997). Nonparametric tests of profit maximization in oligopoly with application to the beef packing industry. *American Journal of Agricultural Economics*, 79(3), 872-879.

Garrett, T. A. (2003). Aggregated versus disaggregated data in regression analysis: implications for inference. *Economics Letters*, 81(1), 61-65.

Halvorsen, B., & Larsen, B. M. (2013). How serious is the aggregation problem? An empirical illustration. *Applied Economics*, 45(26), 3786-3794.

Hashem Pesaran, M. (2003). Aggregation of linear dynamic models: an application to life-cycle consumption models under habit formation. *Economic Modelling*, 20(2), 383-415. doi:10.1016/s0264-9993(02)00059-7

Heckelman, J. C., & Sullivan, T. S. (2002). *Testing for aggregation bias in a non-linear framework: Some Monte Carlo results*. Mimeo, Winston-Salem, Edwardsville..

Hildenbrand, W., & Kneip, A. (1999). Demand aggregation under structural stability. *Journal of Mathematical Economics*, 31(1), 81-109.

Hildenbrand, W., & Kneip, A. (2005). Aggregate behavior and microdata. *Games and Economic Behavior*, 50(1), 3-27.

Imbs, J., Mumtaz, H., Ravn, M. O., & Rey, H. (2005). PPP strikes back: Aggregation and the real exchange rate. *The Quarterly Journal of Economics*, 120(1), 1-43.

Ji, I., Chung, C., & Lee, J. (2017). Measuring Oligopsony Power in the US Cattle Procurement Market: Packer Concentration, Cattle Cycle, and Seasonality. *Agribusiness*, 33(1), 16-29.

Jorgenson, D., Lau, L. J., Stoker, T. M., Basmann, R., & Rhodes, G. (1982). The transcendental logarithmic model of aggregate consumer behavior. *Advances in econometrics*.

Kelejian, H. H. (1995). Aggregated heterogeneous dependent data and the logit model: A suggested approach. *Economics Letters*, 47(3-4), 243-248.

Koontz, S. R., & Garcia, P. (1997). Meat-packer conduct in fed cattle pricing: multiple-market oligopsony power. Journal of Agricultural and Resource Economics, 87-103.

Koontz, S. R., Garcia, P., & Hudson, M. A. (1993). Meatpacker conduct in fed cattle pricing: An investigation of oligopsony power. *American Journal of Agricultural Economics*, 75(3), 537-548.

Lewbel, A. (1992). Aggregation with log-linear models. *The Review of Economic Studies*, 59(3), 635-642.

Lopez, R. A., Azzam, A. M., & Lirón-España, C. (2002). Market power and/or efficiency: A structural approach. *Review of Industrial Organization*, 20(2), 115-126.

Maddala, G. (1977). Self-selectivity problems in econometric models. *Applications of Statistics*, 351-366.

Mittelhammer, R. C., Shi, H., & Wahl, T. I. (1996). Accounting for aggregation bias in almost ideal demand systems. *Journal of Agricultural and Resource Economics*, 247-262.

Moeltner, K. (2003). Addressing aggregation bias in zonal recreation models. *Journal of Environmental Economics and Management*, 45(1), 128-144.

Morrison Paul, C. J. (2001). Market and cost structure in the US beef packing industry: a plant-level analysis. *American Journal of Agricultural Economics*, 83(1), 64-76.

Muth, M. K., & Wohlgenant, M. K. (1999). Measuring the degree of oligopsony power in the beef packing industry in the absence of marketing input quantity data. *Journal of Agricultural and Resource Economics*, 299-312.

Nickell, S. (1981). Biases in dynamic models with fixed effects. Econometrica: *Journal of the Econometric Society*, 1417-1426.

Nicoletti, C., & Best, N. (2012). Quantile regression with aggregated data. *Economics Letters*, 117(2), 401-404.

Paluch, M., & Schiffbauer, M. (2007). Distributional effects of capital and labor on economic growth (Bonn econ discussion papers).

Pesaran, M. H., & Chudik, A. (2014). Aggregation in large dynamic panels. *Journal of Econometrics*, 178, 273-285. doi:10.1016/j.jeconom.2013.08.027

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 79-113.

Progressive Grocer Magazine, Progressor Grocer. Internet site:http:// https://progressivegrocer.com/

Schroeter, J., & Azzam, A. (1990). Measuring market power in multi-product oligopolies: the US meat industry. *Applied Economics*, 22(10), 1365-1376.

Schroeter, J., & Azzam, A. (1991). Marketing margins, market power, and price uncertainty. *American Journal of Agricultural Economics*, 73(4), 990-999.

Schroeter, J. R. (1988). Estimating the degree of market power in the beef packing industry. *The Review of Economics and Statistics*, 158-162.

Schroeter, J. R., Azzam, A. M., & Zhang, M. (2000). Measuring market power in bilateral oligopoly: the wholesale market for beef. *Southern Economic Journal*, 526-547.

Stiegert, K. W., Azzam, A., & Brorsen, B. W. (1993). Markdown pricing and cattle supply in the beef packing industry. *American Journal of Agricultural Economics*, 75(3), 549-558.

Stoker, T. M. (1984). Completeness, distribution restrictions, and the form of aggregate functions. Econometrica: *Journal of the Econometric Society*, 887-907.

Stoker, T. M. (1986). Consistent estimation of scaled coefficients. Econometrica: *Journal of the Econometric Society*, 1461-1481.

Stoker, T. M. (1993). Empirical approaches to the problem of aggregation over individuals. *Journal of Economic literature*, 31(4), 1827-1874.

Tenn, S. (2006). Avoiding aggregation bias in demand estimation: A multivariate promotional disaggregation approach. *Quantitative Marketing and Economics*, 4(4), 383-405.

Theil, H., & Theil, H. (1971). *Principles of econometrics*. Retrieved from

U.S. Department of Agriculture. Economic Research Service. Meat Price Spreads. Internet site: https://www.ers.usda.gov/data-products/livestock-meat-domestic-data/

U.S. Department of Agriculture. Grain Inspection, Packers and Stockyards Administration. *Packers and Stockyards Programs Annual Reports*. Internet site: https://www.ams.usda.gov/reports/psd-annual-reports

U.S. Department of Agriculture. Economics, Statistics and Market information System. Livestock Slaughter Annual Summary. Internet site: http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1097

U.S. Department of Labor. Bureau of Labor Statistics. Internet site: http://www.bls.gov

Van Garderen, K. J., Lee, K., & Pesaran, M. H. (2000). Cross-sectional aggregation of non-linear models. *Journal of Econometrics*, 95(2), 285-331.

Ward, C. E. (2002). A review of causes for and consequences of economic concentration in the US meatpacking industry. *Current Agriculture*, *Food & Resource Issues*, 3, 1-28.

Weliwita, A., & Azzam, A. (1996). Identifying implicit collusion under declining output demand. *Journal of Agricultural and Resource Economics*, 235-246.

Zellner, A. (1969). On the aggregation problem: A new approach to a troublesome problem *Economic models, estimation and risk programming: Essays in honor of Gerhard Tintner* (pp. 365-374): Springer.

Zheng, X., & Vukina, T. (2009). Do alternative marketing arrangements increase pork packers' market power? *American Journal of Agricultural Economics*, 91(1), 250-263.

Table 1.1. Literature on Market Power in Cattle Procurement

	Study	Data Time	Data Period	Space Aggregation	Industry	Evidence of Market power
1	Schroeter(1988)	Annual	1951-83	U.S.	beef packing	N
2	Azzam and Pagoulatos (1990)	Annual	1959-82	U.S.	Meat Packing (Beef and Pork)	Y
3	Schreoter and Azzam (1990)	Quarterly	1976-86	U.S.	Meat Packing (Beef and Pork)	Y
4	Azzam (1992)	Monthly	1988-91	U.S.	beef packing	Y
5	Azzam and Park (1993)	Annual	1960-77 1982-87	U.S.	beef packing	N Y
6	Koontz, Garcia, and Hudson (1993)	Daily	1980-82 1984-86	Region (state)	beef packing	Y Y (but lower than 80-82)
7	Stiegert, Azzam, and Brorsen (1993)	Quarterly	1972-86	U.S.	beef packing	Y
8	Driscoll, Kambhampaty, and Purcell (1997)	Weekly	1992-93	Region (15 plants)	beef packing	N
9	Muth and Wohlgenant (1999)	Annual	1967-93	U.S.	beef packing	N
10	Schroeter, Azzam,and Zhang (2000)	Monthly	1990-94	U.S.	beef wholesale	N (Little evidence of oligopolistic behavior by meatpacking firms)
11	Paul (2001)	monthly	1992-93	5 Regions	beef packing	N
12	Lopez, Azzam and Liron (2002)	Annual	1972-92	U.S.	Meat Packing (Beef and Pork)	Y
13	Crespi and Sexton (2005)	spot market transaction date	1995-96	Panhandle region	beef packing	Y

Notes: 'Y'means evidence of market power and 'N'means little to no evidence of buyer market power.
This tables is from Ward(2002) and Crespi, Xia, & Jones(2010).

Table 1.2. Summary Statistics of Data

	Mean	S.D.	Median	Maximum	Minimum
Herfindahl Hirschman index for steer and heifer slaughter	0.1606	0.0464	0.1777	0.2096	0.0561
Beef Production (bil. lbs)	2.0397	0.1828	2.0368	2.512	1.653
Cattle Slaughter live weight (bil. lbs)	2.7266	0.2222	2.7204	3.3188	2.2275
National Steers and Heifer Slughter (bil. lbs)	2.6673	0.2852	2.6544	3.329	2.042
Beef Retail Price ($/cwt)	119.74	15.82	118.83	156.41	92.23
Calves Price ($/cwt)	88.7	14.24	89.33	127.51	43.89
Beef Gross Farm Value ($/cwt)	69.23	1.2698	69.21	73.8	62.84
Wholesale price ($/cwt)	80.05	3.3012	79.21	92.31	73.93
Chicken Price ($/cwt)	162.16	17.53	164.4	213.64	123
Pork Price ($/cwt)	251.78	18.06	252.5	308.96	220.77
Corn Price ($/bushel)	2.2662	0.4155	2.247	3.3933	1.4851
Sorghum Price ($/bushel)	2.1098	0.4226	2.072	3.5076	1.2125
Gas Price ($/gal)	1.3659	0.3622	1.2222	2.8008	0.8941
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
Material Productivity (2000=100)	90.56	7.8708	90.99	102.57	78.18

Table 1.3. Aggregation Bias of Conjectural Elasticity

	Details	Estimates
Total of estimated conjectural elasticity, $E(\Theta)$		0.1557
Average of micro conjectural elasticity, $\bar{\theta}$		0.1461
Aggregation Bias, $E(\Theta)-\bar{\theta}$		-0.0096
Detail of aggregation Bias	From heterogeneity of parameter	0.0668
	From heterogeneity of cost	0.0043
	From linearly aggregated data for the nonlinear aggregated model	-0.0807
	Sum of Aggregation Bias	-0.0096

Number in parentheses is standard error of conjectural elasticity of aggregated model.

Table 1.4. Summary of Conjectural Elasticity of Each Model

	Aggregated model ($\hat{\theta}$)	Distribution approach		Joint distribution approach	Firm Level Model (Θ)
		Entropy approach	Gamma Distribution		
TL	0.1464***	0.1548***	0.1595***	0.1492***	0.1712
	(0.0075)	(0.0085)	(0.0068)	(0.0089)	(97.6)
GL	0.1099***	0.1008***	0.1147***	0.1119***	0.1536
	(0.0021)	(0.0039)	(0.0026)	(0.0349)	(100.0)
NQ	0.0633***	0.0656***	0.0656***	0.0658***	0.1679
	(0.0143)	(0.0147)	(0.0147)	(0.0174)	(44.7)

1. Number in parentheses is standard error.
2. Number in parentheses of firm level model is percentage of model that conjectural elasticity is statistically significant at 5% level.
3. TL, GL, and NQ represent transcendental logarithmic, generalized Leontief, and normalized quadratic cost function, respectively.

Table 1.5. Estimated Conjectural Elasticity from Trans-log Cost Function

	Aggregated Model		Distribution Approach				Joint Distribution Approach	
			Entropy Approach		Normal Distribution			
Parameter	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
β_K	-5.5092^{***}	0.2049	-5.1923^{***}	0.1891	-5.8439^{***}	0.2077	-5.3464^{***}	0.1949
β_L	3.8037^{***}	0.1570	3.6278^{***}	0.1481	2.4671^{***}	0.1273	3.5429^{***}	0.1444
β_M	-2.5334^{***}	0.0888	-2.8944^{***}	0.0966	-2.1516^{***}	0.0785	-2.3085^{***}	0.0831
β_Y	-5.2412	4.1070	9.0548^{*}	4.4112	4.8772	12.7132	25.4635	36.3096
β_{KK}	-1.0853^{***}	0.2263	-1.0052^{***}	0.2117	-1.0849^{***}	0.1999	-1.0398^{***}	0.2138
β_{LL}	-0.8811^{***}	0.1661	-0.8696^{***}	0.1647	-0.8066^{***}	0.1346	-0.8249^{***}	0.1523
β_{MM}	0.1966^{***}	0.0659	0.2094^{***}	0.0696	0.1916^{***}	0.0493	0.2052^{***}	0.0588
β_{KL}	1.1371^{***}	0.1886	1.1040^{***}	0.1821	1.0602^{***}	0.1552	1.0828^{***}	0.1747
β_{KM}	-0.5532^{***}	0.0740	-0.5808^{***}	0.0782	-0.4687^{***}	0.0548	-0.5239^{***}	0.0683
β_{LM}	0.1530^{*}	0.0703	0.1636^{*}	0.0739	0.0933^{*}	0.0524	0.1267^{*}	0.0636
β_{YK}	4.2836^{***}	0.1353	4.055^{***}	0.1239	4.5181^{***}	0.1356	4.1573^{***}	0.1269
β_{YL}	-2.5384^{***}	0.1057	-2.4097^{***}	0.0993	-1.52^{***}	0.0848	-2.3403^{***}	0.0962
β_{YM}	2.2004^{***}	0.0601	2.4718^{***}	0.0652	1.9146^{***}	0.0534	2.0294^{***}	0.0561
β_{YY}	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
β_{AS}							-0.0653	0.1315

Note: *, **, *** indicate significant at 10%, 5% and 1% level.

Table 1.6. Estimated Conjectural Elasticity from Generalized Leontief Cost Function

	Aggregated Model		Distribution Approach				Joint Distribution Approach	
			Entropy Approach		Normal Distribution			
Parameter	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
β_K	0.1204***	0.0125	0.0007***	0.0002	0.0857***	0.0107	0.0007***	0.0002
β_L	0.0471***	0.0049	-0.0006***	0.0001	0.0749***	0.0083	-0.0006***	0.0001
β_M	0.1149***	0.0114	-0.0001	0.0001	0.1179***	0.0121	0.0000	0.0001
β_{KK}	4.2361***	0.4476	6.3276***	0.5754	5.1440***	0.5778	6.6753***	0.5979
β_{LL}	1.2851***	0.0909	3.4829***	0.3027	2.0516***	0.1639	3.627***	0.3133
β_{MM}	1.5662***	0.1223	3.5415***	0.2224	1.7241***	0.1350	3.5155***	0.2175
β_{KL}	-0.8485***	0.0922	-1.2852***	0.1416	-1.2088***	0.1349	-1.4125***	0.1506
β_{KM}	-1.0668***	0.1085	-1.3351***	0.1506	-1.0601***	0.1297	-1.3689***	0.1550
β_{LM}	0.3774***	0.0443	-0.152*	0.0693	0.2873***	0.0578	-0.1059	0.0720
θ	0.1099***	0.0021	0.1008***	0.0039	0.1147***	0.0026	0.1119***	0.0349
β_{AS}							-25.0773	71.8288

Note: *, **, *** indicate significant at 10%, 5% and 1% level.

Table 1.7. Estimated Conjectural Elasticity from Quadratic Cost Function

	Aggregated Model		Distribution Approach				Joint Distribution Approach	
			Entropy Approach		Normal Distribution			
Parameter	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
β_K	0.9815***	0.0785	0.9775***	0.0796	0.9775***	0.0796	0.987***	0.0757
β_L	2.6213***	0.0893	2.6222***	0.0894	2.6222***	0.0894	2.6212***	0.0893
β_M	3.5233***	0.1601	3.5262***	0.1609	3.5262***	0.1609	3.5107***	0.1549
β_{KK}	0.8941***	0.1183	0.8925***	0.1185	0.8925***	0.1185	0.8874***	0.1246
β_{LL}	-0.0315	0.0787	-0.0305	0.0789	-0.0305	0.0789	-0.0282	0.0811
β_{MM}	0.0198	0.1214	0.0173	0.1217	0.0173	0.1217	0.0200	0.1241
β_{KL}	0.0533	0.0648	0.0529	0.0649	0.0529	0.0649	0.0501	0.0668
β_{KM}	-0.0715	0.1060	-0.0685	0.1066	-0.0685	0.1066	-0.0635	0.1124
β_{LM}	-0.1057	0.0695	-0.1078	0.0698	-0.1078	0.0698	-0.1039	0.0705
β_Y	-7.6602***	2.1963	-7.8503***	2.2500	-7.8503***	2.2500	-7.851***	2.9970
β_{YY}	0.0558***	0.0170	0.0000***	0.0000	0.0578***	0.0181	0.0000***	0.0000
β_{YK}	0.0514***	0.0131	0.052***	0.0134	0.0520***	0.0134	0.0501***	0.0129
β_{YL}	0.0186*	0.0095	0.0187*	0.0095	0.0187*	0.0095	0.0185*	0.0094
β_{YM}	-0.004	0.0171	-0.0042	0.0172	-0.0042	0.0172	-0.0021	0.0159
θ	0.0633***	0.0143	0.0656***	0.0147	0.0656***	0.0147	0.0658***	0.0174
β_{AS}							-0.3449	8.6005

Note: *, **, *** indicate significant at 10%, 5% and 1% level.

APPENDICES

APPENDIX A: Derivation of Equation (10)

The first term of right side equation (9) is

(A-1) $$\sum_{i=1}^{n} s_i \theta_i = n \operatorname{cov}(s_i, \theta_i) + n \cdot \frac{1}{n}\sum_{i=1}^{n} s_i \frac{1}{n}\sum_{i=1}^{n} \theta_i = n \operatorname{cov}(s_i, \theta_i) + \bar{\theta}$$

The aggregated marginal processing cost from equation (9) can be written as

(A-2) $$\sum_{i=1}^{n} MC_i = \frac{n}{y}\left(\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yi} + \frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yKi} \log w_{Ki} + \frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yLi} \log w_{Li} + \frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yMi} \log w_{Mi} + 2\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yiyi} \log y_i \right)$$

The first term of above equation (A-2) is

(A-3) $$\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yi} = \operatorname{cov}(c_i, \beta_{yi}) + \bar{c} \cdot \bar{\beta}_y$$

The second term of equation (A-2) is [1]

(A-4) $$\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yKi} \log w_{Ki} = \operatorname{cov}(c_i, \beta_{yKi} \log w_{Ki}) + \bar{c} \operatorname{cov}(\beta_{yKi}, \log w_{Ki}) + \bar{c}\bar{\beta}_{yK} \log \bar{w}_K^g$$

---

[1] COV(XY, Z)=E(XYZ)-E(XY)E(Z) = E(XYZ)-E(Z){COV(X,Y)+E(X)E(Y)}
=E(XYZ)-E(Z)COV(X,Y)-E(X)E(Y)E(Z)
E(XYZ)= COV(XY, Z)+E(Z)COV(X,Y)+E(X)E(Y)E(Z)

As the same way,

(A-5) $$\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yLi} \log w_{Li} = \mathrm{cov}(c_i, \beta_{yLi} \log w_{Li}) + \bar{c}\,\mathrm{cov}(\beta_{yLi}, \log w_{Li}) + \bar{c}\bar{\beta}_{yL} \log \bar{w}_L^g$$

(A-6) $$\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yMi} \log w_{Mi} = \mathrm{cov}(c_i, \beta_{yMi} \log w_{Mi}) + \bar{c}\,\mathrm{cov}(\beta_{yMi}, \log w_{Mi}) + \bar{c}\bar{\beta}_{yM} \log \bar{w}_M^g$$

(A-7) $$\frac{1}{n}\sum_{i=1}^{n} c_i \beta_{yiyi} \log y_i = \mathrm{cov}(c_i, \beta_{yiyi} \log y_i) + \bar{c}\,\mathrm{cov}(\beta_{yiyi}, \log y_i) + \bar{c}\bar{\beta}_{yy} \log \bar{y}^g$$

The equation (9) with (A-1) and (A-3) to (A-7) can be written as

(A-8) $$P - w = w\varepsilon\{n\,\mathrm{cov}(s_i, \theta_i) + \bar{\theta}\} + \frac{n\bar{c}}{y}\{\bar{\beta}_y + \bar{\beta}_{yK} \log \bar{w}_K^g + \bar{\beta}_{yL} \log \bar{w}_L^g + \bar{\beta}_{yM} \log \bar{w}_M^g + \bar{\beta}_{yy} \log \bar{y}^g\}$$

$$+ \frac{n\bar{c}}{y}\{\mathrm{cov}(\beta_{yKi}, \log w_{Ki}) + \mathrm{cov}(\beta_{yLi}, \log w_{Li}) + \mathrm{cov}(\beta_{yMi}, \log w_{Mi}) + \mathrm{cov}(\beta_{yiyi}, \log y_i)\}$$

$$+ \frac{n}{y}\{\mathrm{cov}(c_i, \beta_{yi}) + \mathrm{cov}(c_i, \beta_{yKi} \log w_{Ki}) + \mathrm{cov}(c_i, \beta_{yLi} \log w_{Li}) + \mathrm{cov}(c_i, \beta_{yMi} \log w_{Mi}) + \mathrm{cov}(c_i, \beta_{yiyi} \log y_i)\}$$

The second term of first line can be derived as[2]

---

[2] Let's assume that

(a) $\omega_i = \ln x_i$.

Then we can write

(b) $\bar{\omega} = \ln \bar{x}^g$. where $\bar{x}$ is arithmetic mean and $\bar{x}^g$ is geometric mean.

From (a), *x* can be expressed as an exponential form and we can apply power series. Then

(c) $x_i = \exp(\omega_i) = \exp(\bar{\omega})\exp(\omega_i - \bar{\omega}) = \exp(\bar{\omega})\left\{\frac{(\omega_i - \bar{\omega})^0}{0!} + \frac{(\omega_i - \bar{\omega})^1}{1!} + \frac{(\omega_i - \bar{\omega})^2}{2!} + \frac{(\omega_i - \bar{\omega})^3}{3!} + \cdots\right\}$.

(A-9) $$\frac{n\bar{c}}{y}\left\{\bar{\beta}_y + \bar{\beta}_{yK}\log\bar{w}_M^g + \bar{\beta}_{yL}\log\bar{w}_M^g + \bar{\beta}_{yM}\log\bar{w}_M^g + \bar{\beta}_{yy}\log\bar{y}^g\right\}$$

$$=\frac{n\bar{c}}{y}\left[\bar{\beta}_y + \bar{\beta}_{yK}\left\{\log\bar{w}_K - \frac{1}{2n}\sum_{i=1}^{n}\left(\log w_{Ki} - \log\bar{w}_K^g\right)^2\right\} + \bar{\beta}_{yL}\left\{\log\bar{w}_L - \frac{1}{2n}\sum_{i=1}^{n}\left(\log w_{Li} - \log\bar{w}_L^g\right)^2\right\}\right.$$

$$\left. + \bar{\beta}_{yM}\left\{\log\bar{w}_M - \frac{1}{2n}\sum_{i=1}^{n}\left(\log w_{Mi} - \log\bar{w}_M^g\right)^2\right\} + \bar{\beta}_{yy}\left\{\log\bar{y} - \frac{1}{2n}\sum_{i=1}^{n}\left(\log y_i - \log\bar{y}^g\right)^2\right\}\right]$$

The equation (A-8) with equation (A-9) is

(A-10) $$P - w = w\varepsilon\bar{\theta} + \frac{c}{y}\left\{\bar{\beta}_y + \bar{\beta}_{yK}\log\bar{w}_K + \bar{\beta}_{yL}\log\bar{w}_L + \bar{\beta}_{yM}\log\bar{w}_M + \bar{\beta}_{yy}\log\bar{y}\right\}$$

$$+\frac{c}{y}\left\{\frac{w\varepsilon}{\bar{c}}\operatorname{cov}(y_i,\theta_i) + \operatorname{cov}(\beta_{yKi},\log w_{Ki}) + \operatorname{cov}(\beta_{yLi},\log w_{Li}) + \operatorname{cov}(\beta_{yMi},\log w_{Mi}) + \operatorname{cov}(\beta_{yiyi},\log y_i)\right\}$$

$$+\frac{n}{y}\left\{\operatorname{cov}(c_i,\beta_{yi}) + \operatorname{cov}(c_i,\beta_{yKi}\log w_{Ki}) + \operatorname{cov}(c_i,\beta_{yLi}\log w_{Li}) + \operatorname{cov}(c_i,\beta_{yMi}\log w_{Mi}) + \operatorname{cov}(c_i,\beta_{yiyi}\log y_i)\right\}$$

$$-\frac{\bar{c}}{2y}\left\{\bar{\beta}_{yK}\sum_{i=1}^{n}\left(\log w_{Ki} - \log\bar{w}_K^g\right)^2 + \bar{\beta}_{yL}\sum_{i=1}^{n}\left(\log w_{Li} - \log\bar{w}_L^g\right)^2 + \bar{\beta}_{yM}\sum_{i=1}^{n}\left(\log w_{Mi} - \log\bar{w}_M^g\right)^2 + \bar{\beta}_{yy}\sum_{i=1}^{n}\left(\log y_i - \log\bar{y}^g\right)^2\right\}$$

$\bar{x} = \bar{x}^g\left\{1 + \frac{1}{n}\sum_{i=1}^{n}\frac{(\omega_i - \varpi)^2}{2!} + \frac{1}{n}\sum_{i=1}^{n}\frac{(\omega_i - \varpi)^3}{3!} + \cdots\right\}$. Let's assume that x_i is log normal distribution, then $\frac{\bar{x}}{\bar{x}^g} \approx \exp\left\{\frac{1}{2n}\sum(\ln x_i - \ln\bar{x}^g)^2\right\}$. We take a log each side and can get

$\log\bar{x}^g = \log\bar{x} - \frac{1}{2n}\sum(\ln x_i - \ln\bar{x}^g)^2$

APPENDIX B: Derivation of Equation (12)

The error term of equation (11) is

(B-1) $$\xi = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(\beta_i - \overline{\beta}\right) + \frac{1}{\overline{c}n}\sum_{i=1}^{n}\left\{\left(X_i - X^c\right)B_i - \left(\overline{X} - X^c\right)\overline{B}\right\}\left(C_i - \overline{C}\right) - \frac{1}{n}\sum_{i=1}^{n} S_{x,ig}^2 \overline{\beta} + \varepsilon$$

The second term of right equation is

(B-2) $$\frac{1}{\overline{c}n}\sum_{i=1}^{n}\left\{\left(X_i - X^c\right)B_i - \left(\overline{X} - X^c\right)\overline{B}\right\}\left(C_i - \overline{C}\right) = \frac{1}{\overline{c}n}\sum_{i=1}^{n}\left\{X_i B_i - X^c B_i - \overline{X}\,\overline{B} + X^c \overline{B}\right\}\left(C_i - \overline{C}\right)$$

$$= \frac{1}{\overline{c}n}\sum_{i=1}^{n}\left\{\left(X_i B_i - \overline{X}\,\overline{B}\right) - X^c\left(B_i - \overline{B}\right)\right\}\left(C_i - \overline{C}\right)$$

$$= \frac{1}{\overline{c}n}\sum_{i=1}^{n}\left(X_i B_i - \overline{X}\,\overline{B}\right)\left(C_i - \overline{C}\right) - \frac{1}{\overline{c}n}\sum_{i=1}^{n} X^c\left(B_i - \overline{B}\right)\left(C_i - \overline{C}\right)$$

The equation (B-1) with equation (B-2) is

(B-3) $$\xi = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(\beta_i - \overline{\beta}\right) + \frac{1}{\overline{c}n}\sum_{i=1}^{n}\left(X_i B_i - \overline{X}\,\overline{B}\right)\left(C_i - \overline{C}\right) - \frac{1}{\overline{c}n}\sum_{i=1}^{n} X^c\left(B_i - \overline{B}\right)\left(C_i - \overline{C}\right) - \frac{1}{n}\sum_{i=1}^{n} S_{x,ig}^2 \overline{\beta} + \varepsilon$$

The $\overline{b}$ of equation (B-3) can be obtained as following equation.

(B-4) $$\overline{b} = \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\overline{X}\overline{\beta} + \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\xi$$

$$= \overline{\beta} + \left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(\beta_i - \overline{\beta}\right) + \frac{1}{\overline{c}n}\left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\sum_{i=1}^{n}\left(X_i B_i - \overline{X}\,\overline{B}\right)\left(C_i - \overline{C}\right)$$

$$- \frac{1}{\overline{c}n}\left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\sum_{i=1}^{n} X^c\left(B_i - \overline{B}\right)\left(C_i - \overline{C}\right) - \frac{1}{n}\left(\overline{X}'\overline{X}\right)^{-1}\overline{X}'\sum_{i=1}^{n} S_{x,ig}^2 \overline{\beta} + \varepsilon$$

The second term of second line at right side of equation (B-4) is

(B-5) $$\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'\frac{1}{n}\sum_{i=1}^{n}\left(X_i-\bar{X}\right)\left(\beta_i-\bar{\beta}\right)=\frac{1}{n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_i\left(\beta_i-\bar{\beta}\right)-\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'\bar{X}\left(\beta_i-\bar{\beta}\right)\right\}$$

$$=\frac{1}{n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_i\left(\beta_i-\bar{\beta}\right)-I\left(\beta_i-\bar{\beta}\right)\right\}$$

$$=\frac{1}{n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_i-I\right\}\beta_i$$

The third term of second line at right side of equation (B-4) is

(B-6) $$\frac{1}{\bar{c}n}\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'\sum_{i=1}^{n}\left(X_iB_i-\bar{X}\,\bar{B}\right)\left(C_i-\bar{C}\right)=\frac{1}{\bar{c}n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_iB_i\left(C_i-\bar{C}\right)-I\bar{B}\left(C_i-\bar{C}\right)\right\}$$

$$=\frac{1}{\bar{c}n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_iB_iC_i-\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_iB_i\bar{C}\right\}$$

$$=\frac{1}{\bar{c}n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X_iB_i\left(C_i-\bar{C}\right)\right\}$$

The first term of third line at right side of equation (B-4) is

(B-7) $$\frac{1}{\bar{c}n}\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'\sum_{i=1}^{n}X^c\left(B_i-\bar{B}\right)\left(C_i-\bar{C}\right)=\frac{1}{\bar{c}n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X^c\left(B_iC_i-B_i\bar{C}\right)\right\}$$

$$=\frac{1}{\bar{c}n}\sum_{i=1}^{n}\left\{\left(\bar{X}'\bar{X}\right)^{-1}\bar{X}'X^cB_i\left(C_i-\bar{C}\right)\right\}$$

The equation (B-4) with equation (B-5), (B-6) and (B) is equation (12)

APPENDIX C: Auxiliary Equation

The following equations are auxiliary equations for equation (15)

(C-1) $\frac{1}{n}\log w_{Kit} = hp_{02i} + hp_{12i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hp_{22i}\log \overline{w}_{Kt} + hp_{32i}\log \overline{w}_{Lt} + hp_{42i}\log \overline{w}_{Mt} + hp_{52i}\log \bar{y}_t$

(C-2) $\frac{1}{n}\log w_{Lit} = hp_{03i} + hp_{13i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hp_{23i}\log \overline{w}_{Kt} + hp_{33i}\log \overline{w}_{Lt} + hp_{43i}\log \overline{w}_{Mt} + hp_{53i}\log \bar{y}_t$

(C-3) $\frac{1}{n}\log w_{Mit} = hp_{04i} + hp_{14i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hp_{24i}\log \overline{w}_{Kt} + hp_{34i}\log \overline{w}_{Lt} + hp_{44i}\log \overline{w}_{Mt} + hp_{54i}\log \bar{y}_t$

(C-4) $\frac{1}{n}\log y_{it} = hp_{05i} + hp_{15i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hp_{25i}\log \overline{w}_{Kt} + hp_{35i}\log \overline{w}_{Lt} + hp_{45i}\log \overline{w}_{Mt} + hp_{55i}\log \bar{y}_t$

(C-5) $\log w_{Kit} = hc_{02i} + hc_{12i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hc_{22i}\log \overline{w}_{Kt} + hc_{32i}\log \overline{w}_{Lt} + hc_{42i}\log \overline{w}_{Mt} + hc_{52i}\log \bar{y}_t$

(C-6) $\log w_{Lit} = hc_{03i} + hc_{13i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hc_{23i}\log \overline{w}_{Kt} + hc_{33i}\log \overline{w}_{Lt} + hc_{43i}\log \overline{w}_{Mt} + hc_{53i}\log \bar{y}_t$

(C-7) $\log w_{Mit} = hc_{04i} + hc_{14i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hc_{24i}\log \overline{w}_{Kt} + hc_{34i}\log \overline{w}_{Lt} + hc_{44i}\log \overline{w}_{Mt} + hc_{54i}\log \bar{y}_t$

(C-8) $\log y_{it} = hc_{05i} + hc_{15i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + hc_{25i}\log \overline{w}_{Kt} + hc_{35i}\log \overline{w}_{Lt} + hc_{45i}\log \overline{w}_{Mt} + hc_{55i}\log \bar{y}_t$

(C-9) $s_{xig}^2\overline{\beta} = r_{0i} + r_{1i}\frac{\varepsilon w}{\bar{c}}\bar{y}_t + r_{2i}\log \overline{w}_{Kt} + r_{3i}\log \overline{w}_{Lt} + r_{4i}\log \overline{w}_{Mt} + r_{5i}\log \bar{y}t$

where $s_{xig}^2\overline{\beta} = \left(\log w_{K\,it} - \log \overline{w}_{Kt}^{g}\right)\overline{\beta}_{yK} + \left(\log w_{Li\,t} - \log \overline{w}_{Lt}^{g}\right)\overline{\beta}_{yL} + \left(\log w_{M\,it} - \log \overline{w}_{Mt}^{g}\right)\overline{\beta}_{yM} + \left(\log y_{it} - \log \bar{y}_t^{g}\right)\overline{\beta}_{yy}$.

A. Parameters Value and Variance-Covariance Matrix used in Monte Carlo Simulation

D-1. Variance-covariance matrix used for generating firm level data

	m	s_{Ki}	s_{Li}	s_{Mi}	ln y
m	0.096				
s_{Ki}	0.037	0.270			
s_{Li}	-0.017	0.459	0.088		
s_{Mi}	-0.005	0.066	0.005	0.033	
ln y	0.734	0.033	0.475	0.222	1.952

D-2. Parameter estimate used for generating firm level data

Parameter	Coefficien	Parameter	Coefficient
β_K	0.284	β_{YY}	2.890
β_L	0.921	β_{YK}	0.027
β_M	1.542	β_{YL}	-0.57
β_{KK}	0.178	β_{YM}	-1.14
β_{LL}	0.224	Θ	0.019
β_{MM}	0.291	α_0	-3.12
β_{KL}	-0.05	η	0.783
β_{KM}	-0.04	α_1	0.093
β_{LM}	-0.08	α_2	0.166
β_Y	-2.36	α_3	-0.04

CHAPTER II

IMPACT OF CAPTIVE SUPPLY ON SPOT PRICE IN THE U.S. CATTLE PROCUREMENT MARKET : A DYNAMIC MODELING APPROACH

ABSTRACT

This paper examines the impact of captive market supply on spot market price in the U.S. cattle procurement market, while considering dynamic interactions between captive and spot markets. Both conceptual analysis and empirical models explore advantages of dynamic models over static models by focusing on the temporal change in the ratio of captive purchase to packers' total procurement and discount factor. Empirical models were estimated using the Kalman filter procedure with three alternative cost functions. Overall, dynamic estimation results found a negative relationship between captive market quantity and spot market prices. However, results of static model showed that the captive market quantity - spot market price relationship was sensitive to assumptions on captive supply and functional forms of cost function. Findings from our empirical analysis clearly suggest that dynamic models are more appropriate than static models in examining the impact of captive supply on spot price in the cattle procurement market.

INTRODUCTION

Recently captive cattle supplies through packer-owned cattle, forward contracts, and marketing agreements have greatly increased from 41% in 2007 to 60% in 2016 in the U.S. cattle procurement market (USDA-GIPSA). For many years, cattle producers have argued that packers' captive cattle supplies harm the fed cattle industry by reducing spot prices. They claim that as beef packers procure the expanded proportion of cattle using captive supplies, their cattle demand from the spot market decreases and as a result, the spot price decreases. Prior studies suggest that when the extent of the reduced demand in the spot market is greater than its supply decrease, the spot price decreases (Azzam 1998; Love and Burton 1999; Schroeter and Azzam 1999; Zhang and Sexton 2000). Other studies claim that the relationship between captive supply and spot prices should be neutral, as curtailed packer demand in the spot market keeps balance with its diminished supply (U.S. General Accounting Office 1987; Hayenga and O'Brien 1991; USDA-AMS 1996). For example, "If a 20% of the demand of fed cattle is removed, so is 20% of the supply, then, the net effect on the market is zero (USDA-AMS 1996, p.30). Overall, the relationship between captive supply and spot market prices has not been clearly determined in the literature (see Table 2.1).

A major reason for this ambiguous result might be that most studies are based on static models that do not consider dynamic interactions between captive and spot supplies. However, in reality, beef packers are likely to determine the cattle procurement quantity from the captive market first and then fill their need from the spot market. Therefore, the optimal cattle procurement in spot market affected by the choice of captive market quantity. This dynamic process should be repeated consecutively, which is very similar to 'repeated game' in dynamic analysis.

Therefore, so-called “new empirical industrial organization (NEIO)” static framework used in earlier studies are not appropriate to simulate dynamic interactions between beef processors and rival firm’s reaction to each other’s quantity or price strategies (Dockner 1992).

There are two basic concepts to the dynamic market framework: strategic (repeated game) and fundamental setting (Perloff, Karp and Golan 2007). It is the strategic setting if firms think that its competitor will react to firm’s present actions in the future. If it is assumed that firms’ present activities change the stock variables that change future profit, then it is referred to fundamental setting. The stock variables can include goodwill, knowledge, and output. Corts (1999) points out that if the firm’s optimization process has dynamics, estimates of market power parameters are sensitive to the discount factor and the persistency of demand. In this case, static model is useful only if firms can modify their strategies instantaneously. However, firms cannot change input quantities that they process rapidly without cost, but also they need large modification costs in inventory and capital input or production (Karp and Perloff 1993a, 1993b; Slade 1995). Demand and supply shifts caused by captive supply are not explicit in static models as interactions between captive and spot markets continue through multi-periods. Therefore, the static model is difficult to capture the shifts of demand and supply in spot market induced by captive supply change (Azzam 1998; Katchova, Sheldon and Miranda 2005; Kutu and Sickles 2012).

The interaction between captive market and spot market exist in cattle procurement and can be represented as ratio of captive market purchase. The ratio of captive market purchase increased constantly year by year from 42.9% in 2003 to 82.2% in 2019 (see Figure 2.1). The influence of captive supply to spot market should increase with the captive supply ratio. Therefore, the change in captive supply ratio and discount rate are used with the Kalman filter estimation procedure are used to reflect the dynamic interactions between captive and spot markets.

OBJECTIVES

This study estimates the impact of captive supply on spot price in the U.S. cattle procurement market using a dynamic modelling approach. First, a conceptual illustration is provided to show that captive supply could either negatively or positively affect cash spot prices depending upon the discount factor and the proportion of packers' beef procurement through captive supply market. Then, an empirical dynamic model is developed to incorporate multi-period interactions between captive and spot market supplies and estimated using the Kalman filter estimation procedure. The model considers the dynamic interactions between captive and spot supplies under assumptions of current both captive and spot supply change.

In the next section we provide a brief literature review on the issue of captive supply effect on the spot prices of the U.S. beef industry. The following section provides conceptual discussions on the importance of using dynamic model for the analysis of the relationship between captive supply and spot prices for the U.S. beef industry. Then, derivation of empirical models and estimation results are discussed. Finally, the last section presents a brief summary of findings and conclusions of this study.

LITERATURE REVIEW

There are a few limited studies in the literature that discuss the impact of captive supply on spot prices in the U.S. cattle procurement market. The empirical estimation results of negative relationship is provided between captive supply and spot prices, but no causal link was examined in these studies (Hayenga and O'Brien 1990, Elam 1992, Schroeder et al 1993).

Some studies develop structural approaches under non-competitive market assumption to find the causal relationship between captive supply and spot prices. Azzam (1998) uses an equilibrium displacement model and finds that captive supply causes a negative effect on cash market price. Burton (1999) argues that a superior downstream firm has an incentive to integrate upstream firms to increase the efficiency of its procurement market, which could affect price of open market price. Burton (1999) points out that the open market price can increase or decrease depending on how integration effect on the supply elasticity of raw material.

Other studies use alternative approaches by focusing on trade attributes other than market conduct. Ward, Koontz and Schroeder (1998) examine the interdependent nature between pre-committed captive supplies and fed cattle prices from the cash market. They found a negative relationship between captive supply and cash prices, and the magnitude was relatively large (between 5% and 35%). Zhang and Sexton (2000) consider high transportation cost as an important key factor in the cattle procurement market and conduct a spatial analysis using a non-cooperative game approach. The study suggests that the captive supply provides geographic buffers that reduce competition among packers but is less effective in reducing packers' competition in markets where the spatial dimension is less important. Schroeter and Azzam (2004) claim that the delivery timing incentive is crucial point in explaining the captive supply-cash market price relationship and find a negative relationship between quantities of captive deliveries and cash market prices. Zheng and Vukina (2009) test whether marketing arrangements (one of captive supply tools) are one way of pork packers' market power exertion in the spot market for live hogs. Although they find the statistically significant market power in the spot market of live hogs, they could not find the evidence that the marketing arrangements have been a source of pork packers' market power exertion in the spot market.

Most previous studies on effects of captive supplies in the beef packing industry have employed either the reduce form model of the structure-conduct-performance paradigm or various econometric structural model associated with the NEIO. Both approaches have faced challenges representing dynamic interactions between captive supplies and spot market cattle prices. The empirical evidence of impacts of captive supplies on spot market cattle prices is not consistent in the literature.

CONCEPTUAL DISCUSSION

This section provides an analytical illustration for the importance of considering interactions between captive and spot markets with dynamic factors such as expectations of discount factor and ratio of captive market purchase procurement. This ratio has increased over time, and cattle procurement from spot market has been affected by captive market. The interaction between captive and spot markets, represented by the ratio of captive purchase, is an important component to reflect repeated games over time for the dynamic model. In addition, the firm's decision making process of multi-period is represented by a packer firm's maximization problem of the current profit and discounted expected future profit at each period. Therefore, the firm's profit making decision process depends on the ratio of captive purchase and discount factor in the dynamic model.

Following Adilov (2010), we assume that all processors can participate in captive market, but processors buy only a proportion of their cattle procurement from the captive supply market. The change in beef processor's captive supply affects rival firm's strategy in the spot market depending upon assumptions on interactions between captive and spot markets and dynamic factors: discount factor (β) and the ratio of captive market purchase (γ) out of total cattle slaughtered in this framework.

Consider the captive market demand given by:

(1) $Q_{c,t} = \gamma\left(a - P_{c,t}\right),$

where $Q_{c,t}$ and $P_{c,t}$ are quantity and price in the captive market for week *t*, respectively.

Then, the inverse residual demand in the spot market is:

(2) $P_{s,t} = a - Q_{s,t} - \gamma\left(a - P_{c,t}\right),$

where $Q_{s,t}$ and $P_{s,t}$ are quantity and price in the spot market for week *t*.

The captive market price ($P_{c,t}$) usually ties the previous week's spot market price (Schroeter and Azzam 2004). Therefore, we assume the relationship between captive and spot markets as $P_{c,t+1} = P_{s,t}$. A processor decides captive and spot supplies in current period t so that it can maximize its discounted stream of profit in the optimization problem. In this case, the profit function of processor *h* for week *t* is:

$$(3) \quad \pi_t^h = \left(P_t^{beef} - P_{c,t}\right) \cdot q_{c,t}^h + \left(P_t^{beef} - P_{s,t}\right) \cdot q_{s,t}^h + \beta \pi_{t+1}^h .$$

where P_t^{beef} is beef price, β is discount factor, $0 < \beta < 1$.

Prices of captive and spot markets can be derived from the first order condition of equation (3).

Then, assuming the steady state price solution, i.e., $P_{s,t} = P_{c,t}$ for all t, we obtain

$$(4) \quad P_{s,t} = \frac{a\left(\gamma^2\beta - 2\gamma\beta + \gamma - 1\right) - 2P_t^{beef}}{\gamma^2\beta - 2\gamma\beta + \gamma - 3} .$$

when γ =0 from equation (4), it is the Cournot-Nash equilibrium solution without considering captive supply. The corresponding demand quantities from captive and spot markets are:

$$(5) \quad Q_c = \frac{2\left(P_t^{beef} - a\right)\gamma}{\gamma^2\beta - 2\gamma\beta + \gamma - 3} \text{ and}$$

$$(6) \quad Q_s = \frac{2\left(P_t^{beef} - a\right)\left(1 - \gamma\right)}{\gamma^2\beta - 2\gamma\beta + \gamma - 3} .$$

To see the effect of packers' captive supply effect on the steady state cash price in the cattle procurement market, we calculate the price difference between spot price ($P_{s,t}$) and price under Cournot competition without considering captive supply ($p_{cournot}$) as:

$$(7)\quad P = P_{s,t} - P_{cournot} = \frac{2\gamma\left(a - P_t^{beef}\right)\left\{1+\left(\gamma-2\right)\beta\right\}}{3\left(\gamma^2\beta - 2\gamma\beta + \gamma - 3\right)}$$

If the equation (7) is negative, then spot price ($P_{s,t}$)is less than price under Cournot competition ($P_{cournot}$) and there exists the price-reducing effect due to the captive supply. Overall, *P* is negative as the ratio of captive market purchase increases under low discount factor. *P* becomes positive with the ratio of captive market purchase when the discount factor is high.

Specifically, the marginal effect of captive market participation ratio (γ) on packers' price-reducing behavior can be calculated as:

$$(8)\quad \frac{\partial p}{\partial \gamma} = \frac{2\left(p_t^{beef} - a\right)\left\{1+2\left(\gamma-1\right)\beta\right\}}{\left(\gamma^2\beta - 2\gamma\beta + \gamma - 3\right)^2}.$$

The value of numerator of equation (8) determine the sign of equation (8). If the sign of $\partial p/\partial \gamma$ is negative, the spot price will decrease as more beef processors participate in the captive market. If the sign of $\partial p/\partial \gamma$ is positive, the spot price will increase as more beef processors participate in the captive market. The packer's price reducing effect increases with the ratio of packers' captive market purchase given discount factor when we account for the interaction between captive and spot markets.

Similarly, we can examine the effect of discount factor (β) on the price-reduction as: as

$$(9)\qquad \frac{\partial p}{\partial \beta} = \frac{2\left(p_t^{beef} - a\right)\left(\gamma - 2\right)\beta}{\left(\gamma^2\beta - 2\gamma\beta + \gamma - 3\right)^2} > 0$$

Equation (9) shows that the spot market price increases with discount factor, which indicates that if packers place more value on profits from captive supplies, the spot market price will increases.

In Figures 2-1 and 2-2, Y and X show that levels of captive supply ratio (reflecting the interaction between captive and spot markets) and discount factor or the direction, either price-decreasing or price-increasing, of captive supply on spot price. As the levels of captive supply ratio and discount factor change over time, the direction of captive supply effect should also change. Therefore, it is appropriate to estimate the empirical dynamic model that incorporates the market interactions as well as the discount factor using

The Kalman filter procedure (Kalman 1960) estimate the dynamic model consecutively to incorporate packers' dynamic decision making process for each time period. The fundamental idea of Kalman filter is that using information about the dynamics of the state, the filter will produce forward and predict what the next state will be. The adjusting or update then involves comparing measurement value with predicted value (Rhudy, Salguero and Holappa 2017).

DERIVATION OF EMPIRICAL DYNAMIC MODEL

The conceptual illustration discussed in the previous section shows the importance of considering interactions between captive and spot markets, the extent of packers' captive supply use for their cattle procurement, and packers' evaluation of discount factor. This section derives an empirical model that can be applied to the U.S. beef procurement market data with multi-time interactions.

A few studies propose reality in decision making in conduct parameter approach with incorporation dynamics (Puller 2007, 2009; Kutlu and Sickles 2011). Puller's two studies focus on fundamental dynamic setting, while Kutlu and Sickles (2011) focus on firm's strategic behavior in repeated games. Firms notice the demand and cost shock before they make their decisions at the starting point of each cycle. Rival firms adjust their output decisions and control profits strategically.

Dynamic models are appropriate when considerable adjustment cost terms in prices or capital accumulation as firm's dynamic behaviors are affected by present and future's demand and supply (Karp and Perloff 1993a, 1993b; Slade 1995; Katchova, Sheldon and Miranda 2005). Therefore, the variable contained dynamic attributes is main difference between static model and dynamic model. If these variables are omitted, estimated parameters are likely to be biased . Firms have information about demand and cost shocks before they make choices at the beginning of each time. Next, the firms choose their strategical choice and these decisions are publicized to others. Then, the oligopoly member react the shocks and modify their quantity decisions strategically. Firms' future profit after the breaking collusion can be decreased by other firms' retaliatory reaction even though firm wants to deviate from collusion currently. In other words, continuity of collusion is up to benefit from breaking the collusion and expected future profit. The firm's deviation is prevented by this process when the firms have high motivation to deviate. This process can be written as:

(10) $$Q_t^*\left(S_t, \beta\right) = \max_{Q_t, S_t} \sum_{i=1}^{n} \pi_t^i\left(s_t^i Q_t ; S_t\right)$$

$$s.t.\ \pi_t^{i,b}\left(Q_t ; S_t\right) + \sum_{k=1}^{\infty} \beta^k E_t\left[\pi_t^{i,r}\left(S_{t+k}\right)\right] < \pi_t^i\left(s_t^i Q_t ; S_t\right) + \sum_{k=1}^{\infty} \beta^k E_t\left[\pi_t^{i,*}\left(S_{t+k}\right)\right], \forall i,$$

where Q_t^* is quantity under collusion, s_t^i is market share of firm i in time t, Q_t is total quantity, $S_t = \left[ds_{c,t}, ds_{s,t}\right]$ represents the state of the market for week *t*; $ds_{c,t}$ and $ds_{s,t}$ are demand shock variable in captive and spot market, $\pi_t^{i,b}$ is the best response profit, $\pi_t^{i,r}$ is the profit for the retaliation period, $\pi_t^{i,*}$ is the profit when firms are collusion, β is discount factor.

The generalized Leontief cost function of beef packing firm *i* for week *t* is written as:

(11) $$c_i = q^i \sum_j \sum_k \beta_{j,k}\left(P_{c,t} P_{s,t}\right)^{0.5},$$

where q^i is firm *i*'s cattle sum of quantity procured in captive market and spot market, *j*, *k* =2, which means captive and spot market, $P_{c,t}$, $P_{s,t}$ is cattle price in captive and spot market in week *t*, respectively. The inverse supply function of live cattle in captive market for week *t* is written as:

(12) $$\log P_{c,t} = \beta_1 + \beta_2 \log Q_{c,t} + \beta_3 \log P_{sub} + \sum_{m=4}^{l} \beta_m \cdot d_m,$$

where $Q_{c,t} = \sum_{i=1}^{n} q_{c,t}^i$, P_{sub} is price of substitute of beef, d_m represents dummy variables for seasonality.

The profit function of firm *i* for week *t* is given as:

(13) $$\pi_t^i = P_t^{beef}\left(q_{c,t}^i + q_{s,t}^i\right) - P_{c,t} q_{c,t}^i - P_{s,t} q_{s,t}^i - q_i \sum_j \sum_k \beta_{j,k}\left(P_{c,t} P_{s,t}\right)^{0.5},$$

where P_t^{beef} is beef price.

From the first order condition with respect to $q_{c,t}^i$ for the equation (13), we have:

$$(14) \quad margin_{c,t} = \theta_t^i \left(\beta_t \, \frac{P_{c,t} q_{c,t}^i}{Q_{c,t}} + \lambda_t \, q_{s,t}^i \right) + \left\{ \beta_{c,c} P_{c,t} + 2\beta_{c,s} \left(P_{c,t} P_{s,t} \right)^{0.5} + \beta_{ss} P_{s,t} \right\},$$

where $margin_{c,t} = P_t^{beef} - P_{c,t}$, means that margin of captive market, $\frac{\partial Q_{c,t}}{\partial q_{c,t}^i} = \theta_i$ is market conduct parameter of captive market, $\frac{\partial P_{c,t}}{\partial Q_{c,t}} \frac{Q_{c,t}}{P_{c,t}} = \beta_2$ is the inverse price elasticity of captive market, $\frac{\partial P_{s,t}}{\partial Q_{c,t}} = \frac{\partial P_{s,t}}{\partial P_{c,t}} \frac{\partial P_{c,t}}{\partial Q_{c,t}} = \lambda_t$ represents the relationship between captive supply change and spot market price change, $q_t^i = q_{c,t}^i + q_{s,t}^i$ is firm *i*'s sum of cattle procurement in captive and spot market.

As mentioned above, λ_t means how much spot market price change if captive supply change and treat as a parameter to be estimated. Assuming $\theta_t^i = \theta_t$ to estimate industry level, equation (14) can be summarized over *N* firms and divided by *N* firms both side. Then, equation (14) for the U.S beef industry becomes:

$$(15) \quad margin_{c,t} = \frac{\theta_t}{N} \left(\beta_2 P_{c,t} + \lambda_t \, Q_{s,t} \right) + \left\{ \beta_{c,c} P_{c,t} + 2\beta_{c,s} \left(P_{c,t} P_{s,t} \right)^{0.5} + \beta_{ss} P_{s,t} \right\},$$

where $Q_t = \sum_{i=1}^{n} q_t^i$, is total cattle procurement in captive and spot market in beef industry.

From equation (15), the marginal effect of captive market margin with respect to cattle supply from spot market, $Q_{s,t,}$ can be derived as:

(16) $$\frac{\partial margin_{c,t}}{\partial Q_{s,t}} = \frac{\theta_t}{N}\lambda_t \ .$$

Equation (16)shows that the additional margin that will be generated by increasing product sales by one unit of spot market quantity. The market conduct parameter (θ_t) and N do not affect the sign as the θ_t has positive value between zero and one and N is also positive value. However, it is not enough interpretation of λ_t as relation between captive quantity and spot prices because $margin_{c,t}$ variable is construct as difference between beef price and captive market cattle price ($margin_{c,t} = P_t^{beef} - P_{c,t}$) as equation (14). And we already find that the ratio of packers' captive market purchase has important role to relation between spot price and captive quantity in equation (8). Therefore, the equation (15) need to have the ratio of packers' captive market purchase and we can divide the equation (15) with total cattle procurement quantity (Q_t) or captive market quantity ($Q_{c,t}$). Then, the equation (15) divided by total cattle procurement quantity (Q_t) is proportion model and written as:

(17) $$margin_{c,t}^{\Pr} = \frac{\theta_t}{N}\left(\beta_2 \frac{P_{c,t}}{Q_t} + \lambda_t \gamma_{s,t}\right) + \left\{\beta_{c,c}\frac{P_{c,t}}{Q_t} + 2\beta_{c,s}\frac{\left(P_{c,t}P_{s,t}\right)^{0.5}}{Q_t} + \beta_{ss}\frac{P_{s,t}}{Q_t}\right\},$$

where $margin_{c,t}^{\Pr} = \frac{margin_{c,t}}{Q_t}$, which means that margin per unit of quantity, $\gamma_{s,t} = \frac{Q_{s,t}}{Q_t}$ which means the ratio of packers' spot market purchase and has inverse relationship with $\gamma_{c,t}$, ratio of packers' spot market purchase as $\gamma_{s,t} = 1 - \gamma_{c,t}$. Then, the marginal effect of captive market margin with respect to ratio of spot market purchase can be obtained as:

(18) $$\frac{\partial margin_{c,t}^{\Pr}}{\partial \gamma_{s,t}} = \frac{\theta_t}{N}\lambda_t \ .$$

Equation (18) is likely to have negative sign as spot market quantity has inverse relationship with captive market quantity.

Equation (15) divided by captive cattle procurement quantity ($Q_{c,t}$) is the relative proportion model, which is written as:

$$(19) \quad margin_{c,t}^{\mathrm{R}} = \frac{\theta_t}{N}\left(\beta_2 \frac{P_{c,t}}{Q_{c,t}} + \lambda_t \gamma_t^R\right) + \left\{\beta_{c,c}\frac{P_{c,t}}{Q_{c,t}} + 2\beta_{c,s}\frac{\left(P_{c,t}P_{s,t}\right)^{0.5}}{Q_{c,t}} + \beta_{ss}\frac{P_{s,t}}{Q_{c,t}}\right\},$$

where $margin_{c,t}^{R} = \dfrac{margin_{c,t}}{Q_{c,t}}$, which means that margin per unit of captive quantity, $\gamma_t^R = \dfrac{Q_{s,t}}{Q_{c,t}}$ which means the relative ratio of packers' spot market purchase to captive market. Then, the marginal effect of captive market margin with respect to relative ratio of spot market purchase is:

$$(20) \quad \frac{\partial margin_{c,t}^{R}}{\partial \gamma_t^R} = \frac{\theta_t}{N}\lambda_t .$$

Extending equation (15) with dynamic consideration, is written as:

$$(21) \quad margin_{c,t} = \frac{\theta_t}{N}\left(\beta_2 P_{c,t} + \lambda_t Q_{s,t}\right) + \left\{\beta_{c,c}P_{c,t} + 2\beta_{c,s}\left(P_{c,t}P_{s,t}\right)^{0.5} + \beta_{ss}P_{s,t}\right\} + \mu_t^*,$$

where μ_t^* is dynamic factor and represent the compatibility constraint in equation (10).Firm's dynamic actions are affected by present demand, future demand, current cost and future cost (Borenstein and Shephard 1996). The continuity of a collusion rely on the gain from deviation and future loss caused by other firm's revenge. Kutlu and Sickles (2012) show that demand shock can be modelled by industry market output divided by expected industry market output for the next period. The future output is used as proxy variables of expected industry market output. The dynamic factor μ_t^* is evaluate the shadow cost of collusion and mean the incentive compatibility constraint in equation (10).

The dynamic factor, μ_t^*, is modelled as a linear function of captive market demand shock ($ds_{c,t}$) and spot market demand shock as:

$$(22) \qquad \mu_t^* \equiv \mu_1 + \mu_2 ds_{c,t} + \mu_3 ds_{s,t},$$

The demand shocks are defined as:

$$(23) \qquad ds_{c,t} = \frac{Q_{c,t}}{Q_{c,t+1}} - mean\left(\frac{Q_{c,t}}{Q_{c,t+1}}\right), \qquad ds_{s,t} = \frac{Q_{s,t}}{Q_{s,t+1}} - mean\left(\frac{Q_{s,t}}{Q_{s,t+1}}\right).$$

Equation (21) has similar form of traditional NEIO model except dynamic attributed term, μ_t^*. The firm plays static game if the μ_t^* is zero for each time period in the equation. In contrast to previous case, the firms play a repeated game if the dynamic attributed term is not zero and can make omitted variable bias if μ_t^* is ignored. The industry conduct is perfect competition if θ_t =0 and μ_t^* =0 and industry conduct is perfect collusion (monopoly) if θ_t =1(Kutlu and Sickles 2012).

The proportion model, Equation (17), and its relative proportion model, Equation (19), with dynamic factor can be written as:

$$(24) \quad margin_{c,t}^{\mathrm{Pr}} = \frac{\theta_t}{N}\left(\beta_2 \frac{P_{c,t}}{Q_t} + \lambda_t \gamma_{s,t}\right) + \left\{\beta_{c,c} \frac{P_{c,t}}{Q_t} + 2\beta_{c,s} \frac{\left(P_{c,t}P_{s,t}\right)^{0.5}}{Q_t} + \beta_{ss} \frac{P_{s,t}}{Q_t}\right\} + \mu_t^*,$$

$$(25) \quad margin_{c,t}^{\mathrm{R}} = \frac{\theta_t}{N}\left(\beta_2 \frac{P_{c,t}}{Q_{c,t}} + \lambda_t \gamma_t^R\right) + \left\{\beta_{c,c} \frac{P_{c,t}}{Q_{c,t}} + 2\beta_{c,s} \frac{\left(P_{c,t}P_{s,t}\right)^{0.5}}{Q_{c,t}} + \beta_{ss} \frac{P_{s,t}}{Q_{c,t}}\right\} + \mu_t^*.$$

The beef packing industry has procured cattle from both non-cash and cash markets, and the ratio of cattle procurement from non-cash market has increased continuously. The market share of non-cash market and cash market from the cattle procurement market are 82.2% and 17.8%, respectively, in 2019. Cattle procurement from non-cash market is through marketing agreement, forward contract, packer-owned cattle Marketing agreement and forward contract has 74.9% and 7.3% of total cattle procurement. The cattle price of marketing agreements are calculated by formulas and these formulas have equations about yield grade, quality grade and carcass weight range. The base price is decided by cash market prices paid the week before delivery of the cattle procured in marketing agreement. For the specific, the base price in five of nine formula is calculated by a week prior delivery price, which was reported in USDA Agricultural Marketing Service (AMS). In the rest four of nine formula, base price is decided at average price level by the packers during the week of delivery of the marketing agreement cattle. The most part of delivery takes usually one week, however small part can takes more days than one weeks[3]. Therefore the price of marketing agreement can be tied up to one or two week prior spot market price.

The forward contract cattle is also one of cattle procurement method on non-cash market. The packer ask feeder delivering cattle of exact heads at designated month in forward contract. When the packers decide the fixed number of cattle at specific delivery week finally, they ask feeder delivering and time lag happens to arrange the transportation[4]. The forward market price is decided by cash sale price, based on the previously agreed basis bid (Ward, Koontz and Schoeder 1996).

As indicated earlier, λ_t in equations (24) and (25) represents s the relationship between captive supply change and spot market price change and its component, the spot and captive

3 .The average delivery date is 6.98 and standard derivation is 3.28 (Schroeter and Azzam 2004).

4. The mean days of from scheduling date to slaughter date is 11.88 days and standard derivation is 7.98 days (Schroeter and Azzam 2004).

market price are affected by their previous prices as mentioned above. Therefore, λ_t is constructed as unobserved time-varying state and is generated by *AR*(1). The equation (21) with (22) can be written as follows and this is base model.

(26) $$margin_{c,t} = \alpha_t \frac{\theta_t}{N} Q_{s,t} + \delta P_{c,t} + \lambda \frac{\theta_t}{N} Q_{s,t} - 2\beta_{c,s} \left(P_{c,t} P_{s,t} \right)^{0.5} - \beta_{ss} P_{s,t} + \mu_1 + \mu_2 ds_{c,t} + \mu_3 ds_{s,t} + \varepsilon_{1t},$$

(27) $$\alpha_{t+1} = \rho \alpha_t + \eta_{1t},$$

where $\delta = \beta_2 \frac{\theta_t}{N} - \beta_{c,c}$, $\lambda \equiv E\left[\lambda_t \,|\Psi \right]$, $\alpha_t \equiv \lambda_t - \lambda$, ε_{1t} is disturbance term of observation equation and ε_{1t} *~N(0, H_ε)*, η_{1t} is disturbance term of state equation, η_{1t} *~N(0, H_η)*

The static form of equation (21) do not have dynamic factor and can be written as:

(28) $$margin_c = \delta P_c + \lambda \frac{\theta_t}{N} Q_s - 2\beta_{c,s} \left(P_c P_s \right)^{0.5} - \beta_{ss} P_s$$

The dynamic model equation (26) and static model equation (28) have some differences. Firstly, the dynamic factors are considered the dynamic behavior affected by present and future demand. Secondly, The equation sets are estimated by Kalman filter algorithm to reflect the dynamic interaction. If the μ_t^* is not significant ($\mu_1 = \mu_2 = \mu_3 = 0$), then the dynamic factors do not reflect the dynamic interactions and vice versa.

The proportion model (equation 24) can be written as same way:

(29) $$margin_{c,t}^{\Pr} = \alpha_t \frac{\theta_t}{N} \gamma_t + \delta \frac{P_{c,t}}{Q_t} + \lambda \frac{\theta_t}{N} \gamma_t - 2\beta_{c,s} \frac{\left(P_{c,t} P_{s,t} \right)^{0.5}}{Q_t} - \beta_{ss} \frac{P_{s,t}}{Q_t} + \mu_1 + \mu_2 ds_{c,t} + \mu_3 ds_{s,t} + \varepsilon_{2t}$$

(30) $$\alpha_{t+1} = \rho \alpha_t + \eta_{2t}$$

where $\delta = \beta_2 \frac{\theta_t}{N} - \beta_{c,c}$, $\lambda \equiv E\left[\lambda_t \left| \Psi \right.\right]$, $\alpha_t \equiv \lambda_t - \lambda$, ε_{2t} is disturbance term of observation equation and ε_{2t} *~N(0, H*$_{\varepsilon}$*)*, η_{2t} is disturbance term of state equation.

The relative proportion model (equation 25) is constructed same way as

$$(31) \quad margin_{c,t}^R = \alpha_t \frac{\theta_t}{N}\gamma_t^R + \delta \frac{P_{c,t}}{Q_{c,t}} + \lambda \frac{\theta_t}{N}\gamma_t^R - 2\beta_{c,s}\frac{\left(P_{c,t}P_{s,t}\right)^{0.5}}{Q_{c,t}} - \beta_{ss}\frac{P_{s,t}}{Q_{c,t}} + \mu_1 + \mu_2 ds_{c,t} + \mu_3 ds_{s,t} + \varepsilon_{3t}$$

$$(32) \quad \alpha_{t+1} = \rho\alpha_t + \eta_{3t}$$

Another cost function forms, trans-log cost function and quadratic cost function are applied to consider the sensitivity of model. The equation of these cost functions are showed in Appendix A and B. The generalized Leontief cost function, trans-log cost function, quadratic cost function with base model, proportion model, and relative proportion model, total 9 types are estimated and the outcomes are explained in result section.

DATA

Cattle procurement quantity in captive and spot market, price of captive and spot market, wholesale price are from Livestock Marketing Information Center and these datasets are consist weekly and from 1st week of 2003 to 52th week of 2019 (*Livestock Monitor* of LMIC).

Labor, Capital, and material input prices of the beef packing industry are from Industry Productivity and Costs Database of Bureau of Labor Statistics (BLS), United States Department of Labor (USDL). Beef price is from the ERS of the USDA and income is Per Capita GDP of the United States Department of Agriculture (USDA), Grain Inspection, Packer and Stockyards Administration (GIPSA), and the National Agricultural Service (NASS).

The summary statistics of data are displayed in table 2.2. The average cattle procurement of captive market per week is 170 million lbs. and has 59.4% of total cattle procurement. The average spot market procurement is 117 million pound , which is 40.6% of total cattle procurement for the study period.

The average cattle price of captive market is $173.2/cwt and standard deviation is $36.2/cwt. On the contrary, the average spot cattle price is $172.2/cwt and standard deviation is $36.6/cwt. The whole sale price of beef is $180.8/cwt and its standard deviation is $36.5/cwt. The detailed statistics of data are presented in Table 2-2.

ESTIMATION AND RESULTS

Equations (18) and (19) are estimated using the Kalman filter procedure. The Kalman filter model typically include two component equations: 1) observation equation and 2) state transition equation. The relationship between Y_t and α_t is modeled in the observation equation, and the relationship between α_t and α_{t+1} is represented in the state transition model as:

(33) $Y_t = \alpha_t + \varepsilon_t\ ,\ \varepsilon_t \sim N(0, H)$

(34) $\alpha_{t+1} = \alpha_t + u_t\ ,\ u_t \sim N(0, Q)$

(35) $\alpha_1 \sim N(a_1, P_1),$

where ε_t and u_t is noise term of observation equation and state equation and independent mutually, α_1 is initial state value and its mean and variance are a_1 and P_1.

Consider $a_{t+1} = E\left[\alpha_{t+1} \middle| Y_t\right]$, which means that a_{t+1} is the prediction of α_{t+1} conditional on Y_t at time t and $P_{t+1} = \mathrm{var}\left[\alpha_{t+1} \middle| Y_t\right]$, is the conditional variance of α_{t+1}. The one step ahead forecast error, v_t is calculated as $v_t = y_t - a_t$ and its variance, $\mathrm{var}(v_t) = F_t$ is one of component to calculate the Kalman gain. Given a_t and P_t , a_{t+1} and P_{t+1} can be calculated as:

(36) $a_{t+1} = a_t + K_t v_t\ ,$

(37) $P_{t+1} = P_t\ (1 - K_t) + Q,$

where $K_t = \dfrac{P_t}{F_t}$ and defined as Kalman gain, Q is process noise covariance matrix. Then, α_t can be predicted by Y_{t-1}, and a_t (prediction value of α_t) can be updated by using additional information, Y_t with equation (33) and (34). The a_{t+1} (prediction value of α_{t+1}) have same value with a_t at time t ($a_{t|t} = E\left[\alpha_t \middle| Y_t\right]$). Therefore, K_t term in the equation (36) is optimal weight between a_t and v_t. The new observation is more weighted if P_t (conditional variance of α_t) has larger value. As same way, new observation is not reliable and have smaller weight if F_t (variance of forecasting error) has larger value. The P_t value can be updated by using equation (37) and identical logic can be applied in equation (37). The system parameters and initial values can be estimated by maximum likelihood estimation method (Kutlu and Sickles, 2011).

Three alternative cost functions, generalized Leontief, trans-log and quadratic cost functions are considered with the base model, proportion model and relative proportion model. The base model is concerning spot market quantity, proportion model is concerning ratio of spot market purchase to total quantity, and relative proportion model is concerning ratio of spot market purchase to captive quantity.

Estimation results with generalized Leontief cost function are reported in Table 2.3. Estimated λ is negative and statistically significant in all dynamic models. Estimates of λ is -0.0007 and significant at 1% level in base model. Estimates of λ from proportion and relative proportion models are -0.0005 and -0.0001, respectively, which are statistically significant at 1% level. The statistically significant negative values of λ indicates that the spot market price will decrease as captive supply increases, which is consistent with findings from some of previous studies (Schroeder et al. 1993; Azzam 1998; Love and Burton 1999; Schroeter and Azzam 1999; Zhang and Sexton 2000; Schroeter and Azzam 2003; Schroeter and Azzam 2004; Wohlgenant 2010). If the captive market quantity increase one unit, the spot price decrease 7cents/cwt. As the same way, if the captive market purchase ratio increase 1%, the spot price decrease 5cents/cwt. If the relative ratio of captive market purchase increase 1%, the spot price decrease 1cents/cwt.

Estimates of dynamic factor terms, μ_2 and μ_3, are significant at 10% and 1% level, respectively, for the base model. Both μ_2 and μ_3 are significant at 1% level from the proportion model and relative proportion model. Statistically significant dynamic factors shows the importance of using dynamic models over static models. The omitted variables bias should exist if static model is used instead of dynamic model. Estimates of δs are 0.6670, 1.1730 and 1.7077 in each model and significant at 1% level. Estimates of $\beta_{c,s}$ from base model is insignificant. However, estimates of $\beta_{c,s}$ from proportion and relative proportion models are 1.7292 and -0.0046, respectively, which are statistically significant at 1% level. Estimates of $\beta_{s,s}$ from base model is insignificant. However, estimates of $\beta_{s,s}$ from proportion and relative proportion models are -2.0247 and 0.6271, respectively, which are statistically significant at 1% level.

Estimates from static models are also reported in Table 2.3 to compare static results to the estimation results from dynamic results. Overall, estimates of λ from static models show positive values. From the static base model, λ is 0.0002 and statistically significant at 1% level. . The estimates are 0.0003 and 0.1124 and they are both significant at 1% level, which is opposite of outcomes from dynamic models outcomes. Some of previous results also show positive estimates or negative but insignificant. Positive relations are estimated by Hayenga and O'brien(1990), Schroeder et al (1993), Ward, Koontz and Schroeder (1998). Negative but insignificant relations are estimated by Elam(1992), Schroeter and Azzam(2004), Wohlgenant (2010). Estimates of δs from static models show 3.5092, 3.1333 and 16,660.1 and all significant at 1% level. Estimates of $\beta_{c,s}$s are -2.2255, -1.8868 and -8,390.4 and all significant at 1% level. Estimates of $\beta_{s,s}$s are 2.6405, 2.2969 and 0.4382 and all significant at 1% level.

Estimation results with trans-log cost function are presented in Table 2.4. Estimated λs are negative and statically significant value from all dynamic models. Estimate of λ is -0.0008 and significant at 1% level in base model. λs are -0.0009 and -0.0002 and all significant at 1% and 5% level in proportion and relative proportion models . If the captive market quantity increase one unit, the spot price decrease 8cents/cwt. As the same way, if the captive market purchase ratio increase 1%, the spot price decrease 9cents/cwt. If the relative ratio of captive market purchase increase 1%, the spot price decrease 2cents/cwt

Estimates of μ_2 and μ_3 are significant at 1% in all dynamic models. Estimates of δ is -4.0700 and significant at 1% level in base model. Estimates of δs from proportion and relative proportion models are -2.5000 and -2.4778, respectively, which are statistically significant at 5% level. Estimates of β_q is -4.44 and significant at 10% level in base model. Estimates of β_q from proportion and relative proportion models are 10.0000 and 8.5445, respectively, which are statistically significant at 1% level. Estimates of $\beta_{q,c}$ is 1.5700 and significant at 5% level in base model. However, Estimates of $\beta_{q,c}$ from proportion model is insignificant and $\beta_{q,c}$ from relative proportion models are 0.9982 and significant at 10% level. Estimates of $\beta_{q,s}$s are -2.0900, -1.5000 and -1.9277 and all significant at 1% level. Estimates of $\beta_{q,q}$ is 0.9710 and significant at 1% level in base model. However, Estimates of $\beta_{q,q}$ from proportion and relative proportion models are insignificant.

However, estimates of λ in static model are negative from the base model but positive from other two models. The estimate of λ is -0.0003 and significant at 1% level in static base model, but has statistically significant positive values at 0.0002 in static proportion and relative proportion models. Estimates of δs in static model are 2.9211, 5.6802 and 3.8509 and all significant at 1% level. Estimates of β_q in static model are 6.7263, 10.2887 and 4.3955 and all significant at 1% level. Estimates of $\beta_{q,c}$ is 0.4468 and significant at 1% level in base model. Estimates of $\beta_{q,c}$ from proportion and relative proportion models are 0.0002 respectively, which are statistically significant at 10% level. Estimates of $\beta_{q,s}$s are 0.4913, -0.0015 and -0.0015 and all significant at 1% level. Estimates of $\beta_{q,q}$s are -0.8543, 0.5029 and 0.1767 and all significant at 1% level.

The estimation result of quadratic cost function approach is given in Table 2.5. Estimate of λs are -0.0009 and significant at 1% level in dynamic base and proportion models. However, λ has positive value at 0.0004 and significant at 1% in dynamic relative proportion model. If the captive market quantity increase one unit, the spot price decrease 9cents/cwt in base model. As the same way, if the captive market purchase ratio increase 1%, the spot price decrease 9cents/cwt in proportion model. The μ_2 and μ_3 terms are significant at 1% in all dynamic models. Estimates of μ_2 are -24.8, -0.0001 and -0.0002 and all significant at 1% level. Estimates of μ_3 are 16.000, 0.0001 and -0.0001 and all significant at 1% level. Estimates of δs are 0.5260, 0.5120 and 2.1912 and all significant at 1% level. Estimates of $\beta_{q,q}$s are 0.0007, 182.0 and 0.0000 and all significant at 1% level. Estimates of $\beta_{s,q}$s are insignificant in base and proportion model. Estimates of $\beta_{s,q}$ from relative proportion models is -0.9108 which are statistically significant at 1% level.

The parameter estimates of λ in static model shows negative values. Estimates of λ are -0.0007, -0.0006, -0.0002 and significant at 1% level in static base, proportion, relative proportion models. Estimates of δs are 0.3883, 0.0008 and 0.8147 and all significant at 1% level. Estimates of $\beta_{q,q}$s are 0.0009, 0.4845 and 0005 and all significant at 1% level. Estimates of $\beta_{s,q}$s are 0.4318, 0.4022 and 0.4318 and all significant at 1% level.

Most of dynamic estimation results found a negative relationship between captive market quantity and spot market prices. However, results of static model show that signs of λ estimates are sensitive to assumptions on captive supply and functional forms of cost function. Findings from our empirical analysis clearly suggests that dynamic models are more appropriate than static models in examining the impact of captive supply on spot price in the cattle procurement market.

CONCLUSIONS

The objective of this study is to estimate the impact of captive supply on spot price in the U.S. cattle procurement market using a dynamic modelling approach. First, conceptual model showed how the packers' price-reducing behavior through captive supply was sensitive to assumptions on dynamic factors such as expectations of discount factor and ratio of captive market purchase to spot market procurement. The conceptual model showed that captive supply could either negatively or positively affect cash spot prices depending upon the discount factor and the proportion of packers' beef procurement through captive supply market. Then, a dynamic model was developed to incorporate multi-period interactions between captive and spot market supplies

Three types of purchase ratio information were considered in the dynamic estimation model: the base model with captive supply quantity, the proportion model with the ratio of captive purchase to total procurement, and the relative proportion model with the ratio of captive purchase to spot quantity. Additionally, three different types of cost functions: generalized Leontief, trans-log, and quadratic cost function forms were used for the sensitivity analysis. Dynamic models were estimated using the Kalman filter procedure iteratively to address the dynamic interactions between captive and spot supplies.

Most of dynamic estimation results found a negative relationship between captive market quantity and spot market prices. However, results of static model showed that the captive market quantity - spot market price relationship was sensitive to assumptions on captive supply and functional forms of cost function. Findings from our empirical analysis clearly suggests that dynamic models are more appropriate than static models in examining the impact of captive supply on spot price in the cattle procurement market. When the dynamic model is used, the packers' price-lowering effect through captive supply was found in many cases.

REFERENCES

Adilov, N. (2010). Bilateral forward contracts and spot prices. *The Energy Journal*, 67-81.

Allaz, B., and Vila, J.-L. (1993). Cournot competition, forward markets and efficiency. *Journal of Economic theory, 59*(1), 1-16.

Azzam, A. M. (1997). Measuring market power and cost-efficiency effects of industrial concentration. *The Journal of Industrial Economics*, *45*(4), 377-386.

Azzam, A. (1998). Captive supplies, market conduct, and the open-market price. *American Journal of Agricultural Economics, 80*(1), 76-83.

Azzam, A. M., & Anderson, D. G. (1996). Assessing competition in meatpacking: Economic history, theory, and evidence: US Department of Agriculture, Packers and Stockyards Programs, Grain Inspection, Packers and Stockyards Administration.

Concentration, U. A. C. o. A. (1996). Concentration in agriculture: a report of the USDA Advisory Committee on Agricultural Concentration. [Washington, D.C.]: United States Dept. of Agriculture, Agricultural Marketing Service.

Dockner, E. J. (1992). A dynamic theory of conjectural variations. *The Journal of Industrial Economics*, 377-395.

Elam, E. (1992). Cash forward contracting versus hedging of fed cattle, and the impact of cash contracting on cash prices. *Journal of Agricultural and Resource Economics*, 205-217.

Hayenga, M., & O'Brien, D. (1990). Competition for Fed Cattle in Colorado vs. Other Areas: The Impact of the Decline in Packers and Ascent in Contracting. Paper presented at the Proceedings of the NCR Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL.

Hayenga, M. O. B., Dan. (1991). "Packer Competition, Forward Contracting Price Impacts, and the Relevant Market for Fed Cattle. *Staff Papers, 232401*(Virginia Tech, Department of Agricultural and Applied Economics.).

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems..J.Basic Engineering, Transactions ASMA, Series D, 82, 35-45.

Karp, L. S., & Perloff, J. M. (1993a). A dynamic model of oligopoly in the coffee export market. *American Journal of Agricultural Economics, 75*(2), 448-457.

Karp, L. S., & Perloff, J. M. (1993b). Open-loop and feedback models of dynamic oligopoly. *International Journal of Industrial Organization, 11*(3), 369-389.

Katchova, A. L., Sheldon, I. M., & Miranda, M. J. (2005). A dynamic model of oligopoly and oligopsony in the US potato-processing industry. *Agribusiness, 21*(3), 409-428.

Kutlu, L., & Sickles, R. C. (2012). Estimation of market power in the presence of firm level inefficiencies. *Journal of Econometrics, 168*(1), 141-155.

Livestock Marketing Information Center. *Livestock Monitor*. Internet site: lmic.info

Love, H. A., & Burton, D. M. (1999). A Strategic Rationale for Captive Supplies. *Journal of Agricultural and Resource Economics, 24*(1), 1-18.

Office, U. S. G. A. (1987). COMMODITY FUTURES TRADING: Purpose, Use, Impact, and Regulation of Cattle Futures Markets. *RCED-88-30*.

Perloff, J. M., Karp, L. S., & Golan, A. (2007). *Estimating market power and strategies*: Cambridge University Press.

Porter, R. H. (1983). A study of cartel stability: the Joint Executive Committee, 1880-1886. *The Bell Journal of Economics*, 301-314.

Rhudy, M. B., Salguero, R. A., & Holappa, K. (2017). A kalman filtering tutorial for undergraduate students. *International Journal of Computer Science & Engineering Survey*, *8*(1), 1-9.

Selukar, R.(2015). State Space Modeling of Sequence Data. SAS Institute Inc., Cary, NC.

Schroeder, T. C., Jones, R., Mintert, J., & Barkley, A. P. (1993). The impact of forward contracting on fed cattle transaction prices. *Review of Agricultural Economics, 15*(2), 325-337.

Schroeter, J. R. (1988). Estimating the degree of market power in the beef packing industry. *The Review of Economics and Statistics*, 158-162.

Schroeter, J. R., Azzam, A., & Inspection, G. (1999). Econiimetric Analysis of Fed Cattle Procurement in the Texas Panhandle.

Schroeter, J. R., & Azzam, A. (2003). Captive supplies and the spot market price of fed cattle: The plant-level relationship. *Agribusiness: An International Journal*, *19*(4), 489-504.

Schroeter, J. R., & Azzam, A. (2004). Captive supplies and cash market prices for fed cattle: The role of delivery timing incentives. *Agribusiness: An International Journal*, *20*(3), 347-362.

Slade, M. E. (1995). Empirical games: the oligopoly case. *Canadian Journal of Economics*, 368-402.

U.S. Department of Agriculture. Economic Research Service. Meat Price Spreads. Internet site: https://www.ers.usda.gov/data-products/livestock-meat-domestic-data/

U.S. Department of Agriculture. Grain Inspection, Packers and Stockyards Administration. *Packers and Stockyards Programs Annual Reports*. Internet site: https://www.ams.usda.gov/reports/psd-annual-reports

U.S. Department of Agriculture. Economics, Statistics and Market information System. Livestock Slaughter Annual Summary. Internet site: http://usda.mannlib.cornell.edu/ MannUsda/viewDocumentInfo.do?documentID=1097

U.S. Department of Labor. Bureau of Labor Statistics. Internet site: http://www.bls.gov

Ward, C. E. A review of causes for and consequences of economic concentration in the US meatpacking industry.

Ward, C. E., Koontz, S. R., & Schroeder, T. C. (1996). Short-run captive supply relationships with fed cattle transaction prices. *US Department of Agriculture, Grain Inspection, Packers and*

Stockyards Administration.

Ward, C. E., Koontz, S. R., & Schroeder, T. C. (1998). Impacts from captive supplies on fed cattle transaction prices. *Journal of Agricultural and Resource Economics*, 494-514.

Wohlgenant, M. K. (2013). Competition in the US Meatpacking Industry. *Annu. Rev. Resour. Econ., 5*(1), 1-12.

Zhang, M., & Sexton, R. J. (2000). Captive supplies and the cash market price: a spatial markets approach. *Journal of Agricultural and Resource Economics*, *25*(1835-2016-149072), 88-108.

Zheng, X., & Vukina, T. (2009). Do alternative marketing arrangements increase pork packers' market power?. *American Journal of Agricultural Economics*, *91*(1), 250-263.

Table 2.1. Previous Studies on Relationship between Captive Supply and Spot Market Price

	Study	Data	Data Period	Industry	Relationship between captive supply and spot market price
1	Ward (1990)			Beef processing	I
2	Hayenga and O'Brien (1990)			Beef processing	P (Colorado) N (Texas)
3	Elam (1992)	Monthly, State	1988-91	Beef processing	N (national data, Kansas, Colorado) I (Nebraska, Texas)
4	Schroeder et al. (1993)	Transaction, Local	1990	Beef processing	N P (some packer and time periods)
5	Azzam (1998)			Beef processing	N
6	Ward, Koontz and Schroeder (1998)	Transaction, U.S.	1992-93	Beef processing	P (forward contract) N (marketing agreement and packer-fed)
7	Love and Burton (1999)			Beef processing	N
8	Schroeter and Azzam (1999)	Transaction, Regional	1995-96	Beef processing	N
9	Zhang and Sexton (2000)			Beef processing	N
10	Schroeter and Azzam (2003)	Transaction, Regional	1995-96	Beef processing	N (small magnitude)
11	Schroeter and Azzam (2004)	Transaction, Regional	1995-96	Beef processing	N (marketing agreement) I (forward contract)
12	Wohlgenant (2010)	Transaction, Weekly	2001-05	Pork processing	N I (reduced form model)

Notes: 'P' means positive relation, 'N' means positive relation and 'I' means statistically insignificant relationship between captive supply and spot market price.

Table 2.2. Summary Statistics of Data

	Unit	Mean	St.Dev	Maximum	Minimum	Median
Captive Market Cattle Procurement	1,000lbs	170,431	45,207	293,100	21,417	173,120
Spot Market Cattle Procurement	1,000lbs	116,664	47,727	265,239	26,682	109,060
Captive Market Cattle Price	$/cwt	173.2	36.2	266.9	114.7	170.6
Spot Market Cattle Price	$/cwt	172.2	36.6	270.8	117.3	169.3
Wholesale Price	$/cwt	180.8	36.5	263.2	121.7	180.3

Table 2.3. Estimates from Dynamic and Static Models with Generalized Leontief Cost Function

	Dynamic Model			Static Model		
	Base Model	Proportion Model	Relative Proportion Model	Base Model	Proportion Model	Relative Proportion Model
δ	0.6670***	1.1730***	1.7077***	3.5092***	3.1333***	16660.1***
λ	-0.0007***	-0.0005***	-0.0001***	0.0002***	0.0003***	0.1124***
$\beta_{c,s}$	-0.4830	1.7292***	-0.0046***	-2.2255***	-1.8868***	-8390.4***
$\beta_{s,s}$	0.2810	-2.0247***	0.6271***	2.6405***	2.2969***	0.4382***
μ_1	321.00***	0.0008***	0.0004***			
μ_2	-12.500*	-0.0001***	-0.0001***			
μ_3	35.000***	-0.0000***	0.0001***			

Note: It is assumed that θ=0.1, N=20 for simplicity (Azzam 1997). '*', '**', '***' indicate significant at 10%, 5% and 1% level.

Table 2.4. Estimates from Dynamic and Static Models with Trans-log Cost Function

	Dynamic Model			Static Model		
	Base Model	Proportion Model	Relative Proportion Model	Base Model	Proportion Model	Relative Proportion Model
δ	-4.0700***	-2.5000**	-2.4778**	2.9211***	5.6802***	3.8509***
λ	-0.0008***	-0.0009***	-0.0002**	-0.0003***	0.0002***	0.0002***
β_q	-4.4400*	10.0000***	8.5445***	6.7263***	10.2887***	4.3955***
$\beta_{q,c}$	1.5700**	0.6190	0.9982*	0.4468***	0.0002*	0.0002*
$\beta_{q,s}$	-2.0900***	-1.5000***	-1.9277***	0.4913***	-0.0015***	-0.0015***
$\beta_{q,q}$	0.9710***	-0.1640	0.0216	-0.8543***	0.5029***	0.1767***
μ_1	240.00***	0.0007***	0.0004***			
μ_2	-22.900***	-0.0001***	-0.0001***			
μ_3	15.000***	0.0001***	0.0001***			

Note: It is assumed that θ=0.1, N=20 for simplicity (Azzam 1997). '*', '**', '***' indicate significant at 10%, 5% and 1% level.

Table 2.5. Estimates from Dynamic and Static Models with Quadratic Cost Function

	Dynamic Model			Static Model		
	Base Model	Proportion model	Relative Proportion model	Base Model	Proportion model	Relative Proportion model
δ	0.5260***	0.5120***	2.1912***	0.3883***	0.0008***	0.8147***
λ	-0.0009***	-0.0009***	0.0004***	-0.0007***	-0.0006***	-0.0002***
$\beta_{q,q}$	0.0007***	182.00***	0.0000***	0.0009***	0.4845***	0.0005***
$\beta_{s,q}$	-0.1700	-0.1480	-0.9108***	0.4318***	0.4022***	0.4318***
μ_1	176.000***	0.0006***	-0.0001			
μ_2	-24.800***	-0.0001***	-0.0002***			
μ_3	16.000***	0.0001***	-0.0001***			

Note: It is assumed that θ=0.1, N=20 for simplicity (Azzam 1997). '*', '**', '***' indicate significant at 10%, 5% and 1% level.

Figure 2.1. Ratio of Captive and Spot Market Purchases

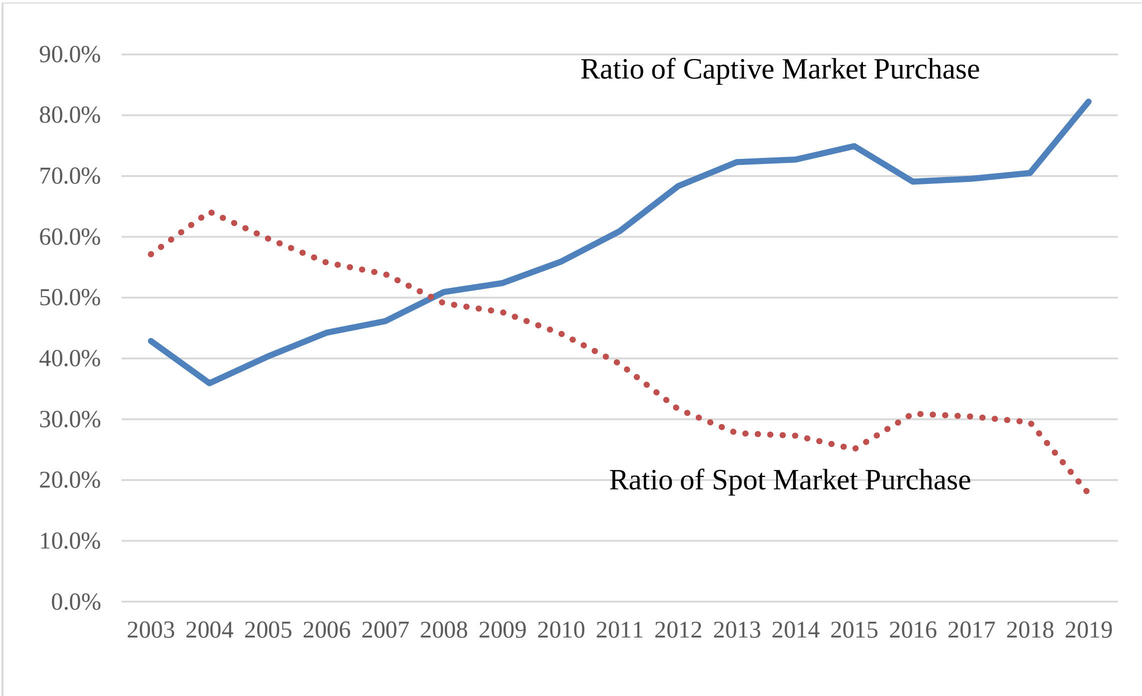


Figure 2.2. Comparison of P_{spot} and $P_{cournot}$ as the Relation between β and γ.

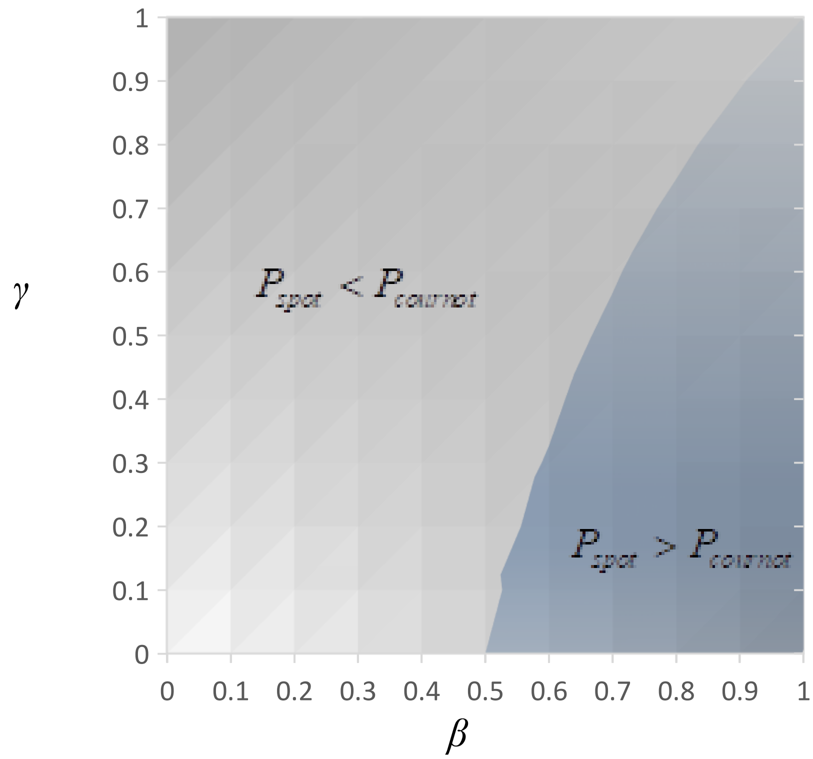
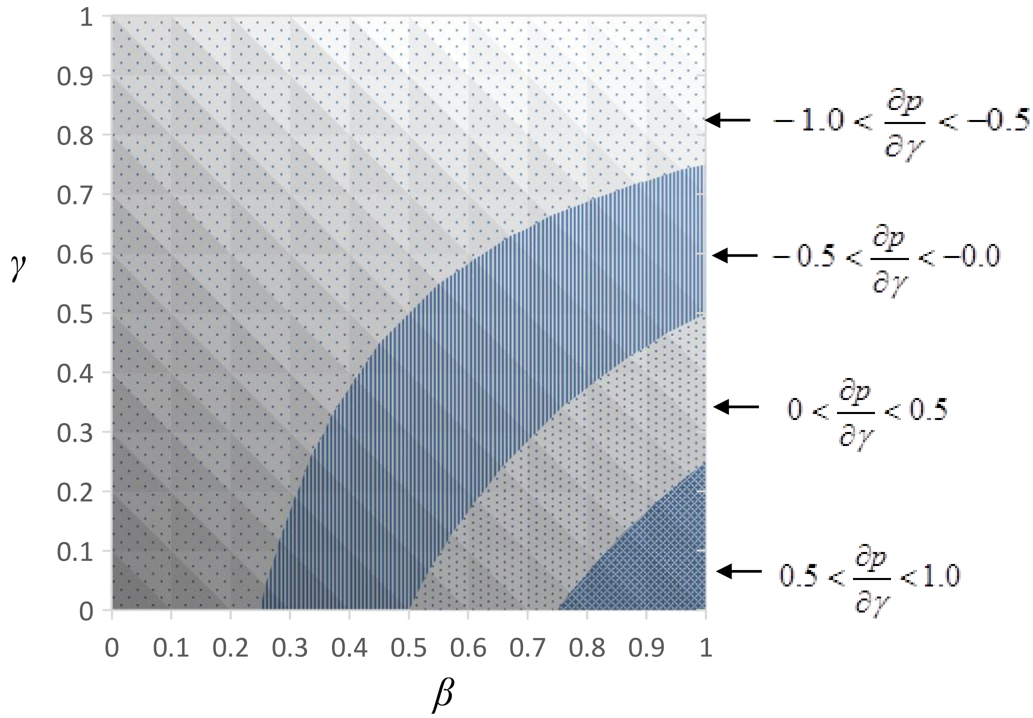


Figure 2.3. Sign of $\partial p/\partial \gamma$ with Processors' Fractional Purchase at Captive Market



APPENDICES

APPENDIX A: Trans-log cost function approach.

Trans-log cost function form is given as:

$$\text{(A-1)}\ \log c_i = \beta_0 + \sum_{j=1}^{2} \beta_j \log P_{j,t} + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} \beta_{jk} \log P_{j,t} \log P_{k,t} + \sum_{j=1}^{2} \beta_j \log q_i \log P_{j,t} + \beta_q \log q_i + \beta_{qq} (\log q_i)^2 ,$$

where q^i is firm *i*'s total cattle procurement and j, *k* are captive or spot market.

The price equation with marginal cost function of (A-1) can be written as:

$$\text{(A-2)}\ margin_{c,t} = \frac{\theta_t}{N}\left(\beta_2 P_{c,t} + \lambda_t Q_{s,t}\right) + \frac{c}{Q_t}\left(\beta_q + \beta_{qc} \log P_{c,t} + \beta_{qs} \log P_{s,t} + 2\beta_{qq} \log Q_t\right) .$$

Then, the base model is:

$$\text{(A-3)}\ margin_{c,t} = \alpha_t \frac{\theta_t}{N} Q_{s,t} + \delta_t P_{c,t} + \frac{\theta_t}{N} \lambda\, Q_{s,t} + \frac{c}{Q}\left(\beta_q + \beta_{qc} \log P_{c,t} + \beta_{qs} \log P_{s,t} + 2\beta_{qq} \log Q\right) + \mu_t^* ,$$

where $\delta_t = \frac{\theta_t}{N} \beta_2$.

The proportion model is:

$$\text{(A-4)}\ margin_{c,t}^{PR} = \alpha_t \frac{\theta_t}{N} \gamma_t + \delta_t \frac{P_{c,t}}{Q_t} + \lambda \frac{\theta_t}{N} \gamma_t + \frac{c}{Q_t^2}\left(\beta_q + \beta_{qc} \log P_{c,t} + \beta_{qs} \log P_{s,t} + 2\beta_{qq} \log Q\right) + \mu_t^* .$$

The relative proportion model is:

$$\text{(A-5)}\ margin_{c,t}^{R} = \alpha_t \frac{\theta_t}{N} \gamma_t^R + \delta_t \frac{P_{c,t}}{Q_{c,t}} + \lambda \frac{\theta_t}{N} \gamma_t^R + \frac{c}{Q_t Q_{c,t}}\left(\beta_q + \beta_{qc} \log P_{c,t} + \beta_{qs} \log P_{s,t} + 2\beta_{qq} \log Q\right) + \mu_t^* .$$

APPENDIX B: Quadratic cost function approach.

The quadratic cost function form is given as:

$$\text{(B-1)} \quad c_i = \sum_j \beta_j P_{j,t} + \beta_q q_i + \frac{1}{2}\left(\sum_j \sum_k \beta_{jk} P_{j,t} P_{k,t} + \beta_{qq} q_i^2 \right) + \sum_j \beta_{jq} P_{j,t} q_i$$

where q^i is firm *i*'s sum of cattle procured in captive market and spot market, *j*, *k* is captive or spot market.

The price equation with marginal cost function of (B-1) can be written as:

$$\text{(B-2)} \quad margin_{c,t} = \frac{\theta_t}{N}\left(\beta_2 P_{c,t} + \lambda_t Q_{s,t}\right) + \left(\beta_{qq} Q + \beta_{cq} P_{c,t} + \beta_{sq} P_{s,t}\right) .$$

The base model is:

$$\text{(B-3)} \quad margin_{c,t} = \alpha_t \frac{\theta_t}{N} Q_{s,t} + \frac{\theta_t}{N}\beta_2 P_{c,t} + \frac{\theta_t}{N}\lambda\, Q_{s,t} + \left(\beta_{qq} Q_t + \beta_{cq} P_{c,t} + \beta_{sq} P_{s,t}\right) + \mu_t^* .$$

The proportion model is:

$$\text{(B-4)} \quad margin_{c,t}^{PR} = \alpha_t \frac{\theta_t}{N}\gamma_t + \delta_t \frac{P_{c,t}}{Q_t} + \frac{\theta_t}{N}\lambda\gamma_t + \beta_{qq} + \beta_{sq}\frac{P_{s,t}}{Q_t} + \mu_t^* ,$$

where $\delta_t = \frac{\theta_t}{N}\beta_2 + \beta_{cq}$.

The relative proportion model is:

$$\text{(B-5)} \quad margin_{c,t}^{R} = \alpha_t \frac{\theta_t}{N}\gamma_t^R + \delta_t P_{c,t} + \lambda\frac{\theta_t}{N}\gamma_t^r + \beta_{qq}\frac{Q_t}{Q_{c,t}} + \beta_{sq}\frac{P_{s,t}}{Q_{c,t}} + \mu_t^* .$$

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