

# Market Power with Dynamic Inventory Constraints: The Bias in Standard Measures

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August 12, 2002

## Abstract

This paper incorporates inventory dynamics into an analysis of market power. Using a model in which each firm accounts for the effect of its current action on the current and future actions of itself and its competitors, we show that measures of market power that ignore inventory dynamics are biased. We then apply the model to the beef-packing industry using annual data on cattle stocks, slaughter and prices from 1933-1999. Our estimates suggest that static measures overestimate the amount of market power exerted by beef-packing firms.

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\*The authors are assistant professors with the Department of Economics at Utah State University. This research was supported by cooperative research agreement 99-ESS with the USDA Grain Inspection, Packers & Stockyards Administration. Opinions expressed are those of the authors and do not necessarily represent the views of the USDA GIPSA. Additional support has been provided by the Utah Agricultural Experiment Station under project number UTA-00011, and by the Research Institute on Livestock Pricing, Virginia Polytechnic and State University. Please send all correspondence regarding this work to Lynn Hunnicutt at [hunnicut@econ.usu.edu](mailto:hunnicut@econ.usu.edu). We thank DeeVon Bailey, John Keith, Arthur Caplan and Kala Krishna for helpful conversations regarding this work. The usual caveat applies.

# 1 Introduction

Many studies of market power are based on measures derived from a static model of competition. For example, in examining market power, the Department of Justice relies on the Lerner index, various concentration ratios, and the Hirschman-Herfindahl index, all of which are derived from a model of competition that assumes firms maximize profits period by period. Intertemporal effects are not easily accounted for in these standard measures. Yet we know that current output choices may affect future possibilities through inventory dynamics. If there is a lag in input production, decisions regarding how much input to use in one period may influence how much is available in the future. Models which account for these inventory dynamics will thus more accurately describe competition. Using an oligopoly/oligopsony model of competition, we provide an exact characterization of how inventory dynamics affect market-power measures. We then apply our model to the beef-packing industry and demonstrate that ignoring inventory dynamics does indeed lead to biased estimates of market power.

Several papers have examined the appropriateness of using a static framework to model dynamic competition (see, for example Pindyck (1985), Riordan (1985), Driskill and McCafferty (1989), Fershtman and Kamien (1987), and Dockner (1992)). The paper most similar to ours is Roberts and Samuelson (1988). They develop a dynamic conjectural variations (CV) model that examines the effect of advertising on product demand. As in our model, advertising affects both current and future profits, which will be recognized by sophisticated firms. There are, however, important differences between the two studies. First, in contrast to Roberts and Samuelson (1988), who compare open and closed-loop equilibrium strategies, we compare a closed-loop equilibrium with one derived from a static model.<sup>1</sup> Since the static model is the standard framework for estimating market power in beef packing, it facilitates easier comparison to others in the literature. Second, our inventory measure is the total U.S. stock of cows, for which data are readily available and which has well-known laws of motion. In contrast, the inventory measure in Roberts and Samuelson (1988) is the stock of consumer goodwill that cigarette advertising generates, for which data are not directly available and dynamics are not well understood.

As in Riordan (1985), Driskill and McCafferty (1989) and Fershtman and Kamien (1987), we find that firms appear more competitive in an explicitly dynamic model than in the standard (static)

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<sup>1</sup>An “open-loop” solution assumes that a firm’s current period choice may affect its rivals’ current period choices and its own future choices, but *not* its rivals’ future choices. A “closed-loop” solution allows all three effects to be non-zero.

CV model. Intuitively, one can think of our model as involving a larger number of “firms” since future versions of all competitors are considered in current decisions. Firm  $i$  must now consider not only its competitor in the current period, but future versions of itself and its competitor. For example, a current increase in purchases of inputs will reduce the inventory of inputs available in the future, increasing future prices. Any attempt to exert current market power by purchasing more inputs without increasing prices will lead to reduced future input availability and ability to exercise market power. Thus “future” versions of firms  $i$  and  $j$  may constrain firm  $i$ ’s current pricing behavior.

Our notion of inventory dynamics arises in industries where there is a lag between the need for an input and its availability. The airline industry faces this problem in two senses. First, delivery of a new plane generally occurs at least a year after the order is placed, so that airlines’ orders need to account for competitors’ current and future responses. Second, simply moving planes and crews between cities occurs with a lag. For example, a plane used to fly from city A to city B may not be immediately available to replace an aircraft with mechanical problems at city C. This potential delay in availability might reduce the number of flights from A to B offered each day in order to reduce the time needed to respond to the problem at city C. Inventory dynamics (associated with ordering new planes or moving planes and crews between cities) often constrain current output choices in a manner that is not captured by static models of oligopoly competition.

Livestock markets provide another good example of inventory dynamics. Cattle markets, for instance, contain a natural intertemporal link since beef cows serve both as consumption goods in beef production and as capital goods in calf production. Rosen, Murphy and Scheinkman (1994) incorporate this intertemporal link in a model designed to explain the regular cycle in U.S. cattle stocks. In their model, ranchers are forward-looking and recognize that current decisions regarding the number of cattle to cull from the herd influence future stocks.<sup>2</sup> It seems reasonable that beef-packing firms also incorporate the cattle cycle into their pricing and marketing decisions (in fact, the USDA Economic Research Service in its *Agricultural Outlook* series describes the link between the cattle cycle and fed beef marketings). As a result, when measuring the market power in industries associated with livestock (such as beef-packing), it is likely that stock dynamics will play an important role.

There is a large literature concerning market power in beef packing. The proliferation of research on this issue is understandable, given that the four-firm concentration ratio in beef packing has

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<sup>2</sup>We use the terms “inventory” and “stock” interchangeably throughout the paper.

increased from below 30% in the early 1970s to 80% in 1996 (Mathews Jr., Hahn, Nelson, Duewer and Gustafson (1999)). Most investigations use the standard CV model which assumes that packing firms consider only current period effects in their livestock purchasing decisions (see, for example, Schroeter (1987), Schroeter and Azzam (1990), Bhuyan and Lopez (1997), Muth and Wohlgenant (1998)).<sup>3</sup> Given the literature cited above, as well as a number of articles that treat cattle stocks as capital goods (Jarvis (1974), Trapp (1986), Rosen et al. (1994) and Nerlove and Fornari (1998)), such an omission is surprising. Indeed, Schroeter and Azzam (1990) note on page 1374 that the standard CV approach “approximate[s] an inherently dynamic problem with a static model.”

Our model gives an exact representation of the bias induced by using a static model to describe dynamic competition. Furthermore, our empirical estimates indicate that this bias is substantially different from zero. As noted above, and consistent with theoretical predictions from alternative models, we find that static (hereafter we refer to them as “myopic”) CV models tend to exaggerate the exercise of market power when applied to markets where dynamic inventory constraints are important.<sup>4</sup>

## 2 Model

### 2.1 The basics

We develop a model that includes the possibility that firms account for inventory dynamics in their optimization problem. In order to generate closed-form solutions, we model two firms ( $i = 1, 2$ ), each choosing how much of an input  $x^i$  to purchase and process in each period. To ease notation, we assume that production involves a Leontief technology, where the input is transformed one-for-one into output. This assumption is without loss of generality, as long as the production function is increasing in  $x^i$ .<sup>5</sup> Let  $X = x^1 + x^2$  denote the aggregate input purchases and the output that

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<sup>3</sup>Koontz, Garcia and Hudson (1993), Azzam and Park (1993), and Weliwita and Azzam (1996) take an entirely different approach and use a repeated game framework to look for collusive behaviour on the part of packing firms.

<sup>4</sup>We do not address the appropriateness of the conduct assumptions made in the CV model. Corts (1999) points out that estimates of market power from a CV model will not accurately describe conduct *unless* firms behave precisely as the model assumes. For example, if firm behavior is not as the Cournot model postulates, conclusions derived from estimating a model of Cournot competition will not be accurate. The weaknesses of the CV approach are well known, yet analyses based on the model continue to be used by many academic economists and policymakers. Given that firms do behave as the Cournot model postulates, our extension produces estimating equations that will lead to a more accurate assessment of market power.

<sup>5</sup>To see this, define the production function for firm  $i$  as  $g(x_t^i)$ . Then, the total amount available for sale is given by  $G(X_t) = \sum_i g(x_t^i)$ , and the demand curve would be given by  $p = p(G(X_t))$ . As long as  $G'(X_t) \geq 0$ , we lose nothing by using  $X_t$  in its place.

is supplied in the period. The inverse demand function is given by  $p = p(X)$ , where  $p'(X) < 0$ . Processing costs incurred by each firm in transforming the raw input into output are  $c(x^i)$ . Inputs are purchased from suppliers following the inverse supply function  $w = w(X, S)$ , where  $S$  represents the stock level in the current period. By including  $S$  in the supply function, we allow for the possibility that input suppliers consider current stock levels, as well as prices when deciding how much to supply. Input prices are positively related to  $X$  ( $w_X > 0$ ) and inversely related to  $S$  ( $w_S < 0$ ). The inverse relationship with stock levels occurs because suppliers are assumed to be willing to sell animals at a lower price when the animal is easily replaced (i.e., when  $S$  is large). Inventory dynamics are represented by the equation  $S_{t+1} = f(S_t, X_t)$ , where  $f_S > 0$  and  $f_X < 0$ .

The objective for firm  $i$  is to choose  $x^i$  each period to maximize the present value of the sum of per-period operating profits,  $\pi_t(p, w) = p(X_t)x^i - w(X_t, S_t)x^i - c(x^i)$ , subject to the inventory dynamics, the actions of rival firm  $j$ , and  $S_0$  given. This discounted profit stream is given by

$$\sum_{t=0}^{\infty} \beta^t \pi_t(p, w)$$

where  $\beta = 1/(1 + \rho)$  and  $\rho$  is the market rate of interest.

There are three effects to consider in this model. The first is the standard oligopoly/oligopsony effect – the current quantity choice made by firm  $i$  affects the current profits of firm  $j$  ( $i \neq j$ ) and therefore firm  $j$ 's current choice. This effect occurs within each period. The next two effects arise because the current quantity chosen by firm  $i$  affects input supplies available in the future. The direct dynamic externality (DDE) arises because the current choice of  $x^i$  affects the future stock and therefore firm  $i$ 's own future input choices. The indirect dynamic externality (IDE) occurs because the current choice of  $x^i$  also affects firm  $j$ 's future input choices, again through the effect on future stocks. We call the first externality “direct” because it gives the effect of  $i$ 's *future* choices on its own current choice. The “indirect” externality gives the effect of firm  $j$ 's *future* choices on firm  $i$ 's current choice.

To incorporate these dynamic externalities, we assume that firm  $i$  believes that its rival's quantity is given by  $x^j = x^j(x^i, S)$ . Consistent with standard oligopoly/oligopsony models, let  $r^j \equiv dx^j(x^i, S)/dx^i$  denote the rate at which firm  $j$ 's quantity adjusts with  $x^i$ , and let  $R^i \equiv dX/dx^i = 1 + r^j$  denote the rate at which market output adjusts with  $x^i$ . Finally, let  $\varepsilon$  and  $\eta$  denote the price elasticity of demand ( $p(X)/Xp'(X)$ ) and the input cost elasticity of supply ( $w(X, S)/Xw_X(X, S)$ ), respectively. It is common to express the rate at which market output adjusts with  $x^i$  in elasticity form,  $\theta^i = (x^i dX)/(dx^i X) = x^i R^i / X$ ; thus  $\theta^i$  is the conjectural elasticity

parameter for firm  $i$ .

Using two firms allows for an exact characterization of the effect of dynamic considerations. Modeling competition between three or more firms makes the theoretic framework intractable, because firms may now have conjectures about other firms' conjectures. The problem of more than two firms is indirectly addressed in Bresnahan (1989), who notes that conjectures in industries with more than two competitors can be estimated using a duopoly/duopsony framework if one assumes that all firms have the same conjecture in a given period or that each firm's conjecture does not change over time. Due to data limitations, we make the first assumption. As suggested by Bresnahan (1989), this allows us to reduce the oligopoly model to two firms – firm  $i$  (the one being studied) and firm  $j$  (any one of the other firms). The second assumption was used by Roberts and Samuelson (1988), who estimated a dynamic CV model of advertising in the cigarette industry. This approach requires disaggregated data with information regarding individual firms, observed over time. Given such a panel data set, one could test both the assumption of identical conjectures across firms and identical conjectures over time.

## 2.2 Deriving the dynamic market-power measures

We study the equilibrium market outcome under a closed-loop solution. The closed-loop output policy will identify each firm's optimal quantity as a function of the current period cattle stock,  $x_t^i = x^i(S_t)$ . Because firm  $i$  understands that  $j$ 's quantity decision is also conditional on  $S_t$ , the closed-loop conjecture (firm  $i$ 's belief about what firm  $j$  considers in its choice) is  $x^j(x^i(S_t), S_t)$ . Aggregate quantity in the market, according to firm  $i$ , is thus  $X(S_t) = x^i(S_t) + x^j(x^i(S_t), S_t)$ .

From firm  $i$ 's first-order condition for profit maximization, we derive equation (1), which gives the marginal value of the last unit of stock used in period  $t$  ( $A_t$ ):

$$A_t = -\beta f_X R_t^i \left[ A_{t+1} \frac{dx_{t+1}^i}{dS_{t+1}} + N_{t+1} \frac{\partial x_{t+1}^j}{\partial S_{t+1}} - w_{S,t+1} x_{t+1}^i \right] \quad (1)$$

where functional dependence on  $X$  and  $S$  is implied,  $A_t = p_t - w_t - c_t'(x_t^i) + (p_t' - w_{X,t})x_t^i R_t^i$  and  $N_{t+1} = (p_{t+1}' - w_{X,t+1})x_{t+1}^i$ . To obtain this equation, we substitute firm  $i$ 's belief about aggregate market quantity into its profit function and simplify the resulting first-order condition. Because the algebra is straightforward but tedious, the derivation is deferred to appendix A.

Equation 1 is the analog to a standard investment rule. It says that firm  $i$  equates marginal profits across periods. As noted, the left-hand side ( $A_t$ ) is the marginal value of the last unit of

stock used in current production. It includes the oligopoly (oligopsony) effect. The right-hand side is the marginal value of foregone input use (i.e., the marginal value of an investment in input stock). This term includes the discounted change in inventory levels ( $-\beta f_X R_t^i$ ), the DDE or the effect of  $x_t^i$  on  $x_{t+1}^i$  through stocks ( $A_{t+1}(dx_{t+1}^i/dS_{t+1})$ ), the IDE or the effect of  $x_t^i$  on  $x_{t+1}^j$  through stocks ( $N_{t+1}(\partial x_{t+1}^j/\partial S_{t+1})$ ), and firm  $i$ 's consideration of input supplier response to a change in inventory levels ( $w_{S,t+1}x_{t+1}^i$ ).

Equation 1 can be expressed in a more familiar way as the closed-loop Lerner index (also derived in appendix A),

$$\mathcal{L}^c = -\frac{\theta_t^i}{\varepsilon_t} + \Delta \quad (2)$$

where  $\mathcal{L}^c = (p_t - w_t - w_{X,t}x_t^i R_t^i - c_t')/p_t$  and  $\Delta = -(\beta f_X R_t^i/p_t)[A_{t+1}(dx_{t+1}^i/dS_{t+1}) + N_{t+1}(\partial x_{t+1}^j/\partial S_{t+1}) - w_{S,t+1}x_{t+1}^i]$ .

The first right-hand term ( $-\theta_t^i/\varepsilon_t$ ) is the Lerner index that is commonly estimated in myopic models of market power. The second term,  $\Delta$ , represents the consideration firm  $i$  gives to the effect of its current choices on future choices through changes in the inventories. Assuming that  $\Delta$  is not zero, the myopic measure of market power ( $-\theta_t^i/\varepsilon_t$ ) does not accurately describe the amount by which firms are able to raise price above marginal cost.

The myopic index accurately describes market power in a few special cases. First, if firms do not care about future returns ( $\beta = 0$ ), equation 2 collapses to the myopic Lerner index. Second, the Lerner index is equal to zero in a competitive market, which occurs when  $R^i = \theta^i = 0$  (i.e., when individual firms realize that their output decisions do not affect market quantity  $X$ ). Under perfect competition the forward-looking Lerner index is equivalent to the myopic index (both are zero) because firms cannot be assured that they will be the claimants of the returns from investing in the stock. Third,  $\Delta = 0$  could occur if the DDE, IDE and input suppliers' reaction cancel one another out, which is unlikely (as noted by Dockner (1992)).

Equation 1 can also be manipulated to measure market power in the input market. Let  $\mathcal{M}^c$  denote the difference between marginal revenue product (net of marginal processing cost) and input price, normalized by the input price. Then, as we derive in appendix A,

$$\mathcal{M}^c = \frac{\theta_t^i}{\eta_t} + \Gamma \quad (3)$$

where  $\mathcal{M}^c = (p_t - w_t + p_t'x_t^i R_t^i - c_t')/w_t$  and  $\Gamma = -(\beta f_X R_t^i/w_t)[A_{t+1}(dx_{t+1}^i/dS_{t+1}) + N_{t+1}(\partial x_{t+1}^j/\partial S_{t+1}) - w_{S,t+1}x_{t+1}^i]$ .

As with the Lerner index,  $\mathcal{M}^c$  is equal to the myopic measure  $\theta_t^i/\eta_t$  plus an adjustment that accounts for the value of investing in the stock. The adjustment includes the DDE, IDE, and anticipated input supplier response. As with the Lerner index, this adjustment term is unlikely to be zero. Models that do not include the discounted profit stream in the firm's maximization problem will not include this adjustment and may therefore draw inaccurate conclusions regarding market power.

### 2.3 Determining the bias in myopic market-power measures

The forward-looking market-power measures given in equations 2 and 3 indicate that myopic models are likely to produce biased estimates of market power. Unfortunately, the direction of the bias is not pinned down by theory. We see that the closed-loop Lerner index ( $\mathcal{L}^c$ ) is smaller than the corresponding static measure ( $\mathcal{L}^s = -\theta_t^i/\varepsilon_t$ ) if and only if  $\Delta$  is negative. Recall that  $\Delta = -(\beta f_X R_t^i/p_t)[A_{t+1}(dx_{t+1}^i/dS_{t+1}) + N_{t+1}(\partial x_{t+1}^j/\partial S_{t+1}) - w_{S,t+1}x_{t+1}^i]$ . We know that  $-\beta f_X/p_t$  is positive. It seems reasonable that market output (input use) will not decrease with an increase in firm  $i$ 's input use, since competitors are not likely to overcompensate for changes firm  $i$  makes. If we make this assumption, then  $R_t^i > 0$  and the myopic Lerner index is biased upward (i.e. the closed-loop index is smaller than the myopic index) if and only if  $[A_{t+1}(dx_{t+1}^i/dS_{t+1}) + N_{t+1}(\partial x_{t+1}^j/\partial S_{t+1}) - w_{S,t+1}x_{t+1}^i] < 0$ . Substituting in for  $A_{t+1}$  and  $N_{t+1}$ , this condition is equivalent to

$$\begin{aligned} & [(p_{t+1} - w_{t+1} - c'_{t+1}) + \{p'_{t+1} - w_{X,t+1}\} x_{t+1}^i R_{t+1}^i] \frac{dx_{t+1}^i}{dS_{t+1}} + \\ & \{p'_{t+1} - w_{X,t+1}\} x_{t+1}^i \frac{\partial x_{t+1}^j}{\partial S_{t+1}} - w_{S,t+1} x_{t+1}^i < 0. \end{aligned} \quad (4)$$

The direction of the bias thus depends on the sign and relative magnitudes of the three terms in equation 4. The sign of the first term is indeterminate in our dynamic framework (although it would be zero in a static model because it includes the first-order condition for period-by-period profit maximization). If demand and supply curves have standard slopes,  $p'_{t+1} - w_{X,t+1}$  is negative. Thus, the second term is negative as long as firm  $j$ 's input use responses are positively related to changes in stock levels. The third term is positive because  $w_S < 0$ . Therefore, the overall bias is the sum of three terms – one of indeterminate sign, one likely negative, and one positive. As a result, the direction and size of the bias in the myopic Lerner index are not determined within the model and become an empirical matter.

Similar calculations for signing the bias can be performed on the myopic measure of input market power. Using the same techniques as for the Lerner index, we can show that  $\mathcal{M}^c < \mathcal{M}^s$  if and only if

$$A_{t+1}(dx_{t+1}^i/dS_{t+1}) + N_{t+1}(\partial x_{t+1}^j/\partial S_{t+1}) - w_{S,t+1}x_{t+1}^i < 0. \quad (5)$$

Since both  $p$  and  $w$  are positive, the bias in the input market-power measure has the same sign as the bias in the Lerner index. As before, signing this bias is an empirical matter.

### 3 Estimating the model

#### 3.1 Deriving the empirical specification

The theoretical results presented above suggest that market-power measures based on myopic CV models are biased. In this section we apply our forward-looking model of competition to the U.S. beef-packing industry to estimate the sign and magnitude of the bias.

Our first task is to derive econometric equations based on the theoretical conditions provided above. Before doing so, a note on cattle production is appropriate. One of the most important decisions for cattle producers is whether to send female calves to slaughter or retain them for addition to their breeding stock. Most of the female calves sent to slaughter are not slaughtered immediately but rather go through a process called *backgrounding* and *finishing*. Backgrounding typically involves a four to six month period when a weaned calf is maintained on pasture or harvested forage before entering the feedlot. Finishing then involves transferring the animal to a feedlot where it will be fed high-concentrate grains for another four to six months.<sup>6</sup> We refer to the meat from these animals as “fed beef.”

Heifers that are not sent to slaughter typically become part of the producer’s breeding stock. Breeding cows can produce at most a single calf per year, have a gestation period of nine months, and are typically bred for the first time in their second or third year of life. A breeding cow may then be retained and bred in subsequent years until approximately her tenth year. At this point, her reproductive abilities begin to deteriorate. Culled cows are sent directly to slaughter as their beef is of lower quality and is not suitable for finishing. We refer to the meat from culled cows as “non-fed beef.” We focus our attention on the fed-beef market, because it makes up approximately

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<sup>6</sup>We assume that backgrounding and finishing of animals is completed by the cattle producers. This simplifies the analysis by removing the need to explicitly model feedlot behavior. Furthermore, it becomes more straightforward to conceptualize how cattle producers respond to current price signals by changing the number of fed heifers sent to the packers.

80% of the domestic market for beef (although we do account for cull cows in the stock-dynamic equation below).

A single “period” in the theoretical section represents three years in the cattle industry, as there is approximately a three-year lag between the investment decision (retention of a cow) and the resulting output (slaughter of her offspring). Since we use annual data in the empirical section, we reformulate the theoretical model so that a period is one year long, and stock dynamics take place over several years. Thus, a cow that is bred at the beginning of period  $t$  will produce offspring that may be marketed at the end of period  $t + 2$  or bred at the beginning of period  $t + 3$ . We specify the following three-year lag structure for stock dynamics

$$S_{t+1} = \gamma_0 S_t + \gamma_2 S_{t-2} - X_t \quad (6)$$

where  $S_t$  is the stock of breeding females (cows) at time  $t$ ,  $X_t$  is the number of young females (heifers) slaughtered at the end of period  $t$ ,  $\gamma_0 = (1 - \delta)(1 - \alpha)$ ,  $\gamma_2 = (1 - \delta)^2 0.5g$ ,  $\delta$  is the death rate,  $g$  is the birthing rate,  $\alpha$  is the cull rate for cows (i.e., fraction of the cow stock slaughtered each period). The intuition behind equation 6 is clear and is similar to the laws of motion for cattle inventories in Rosen et al. (1994) and Baak (1999). The total stock of cows can change for two reasons: (1) cows from period  $t$  may die or get sent to slaughter ( $\gamma_0 S_t$ ) and (2) female calves born from cows bred in period  $t - 2$  that do not die ( $\gamma_2 S_{t-2}$ ) or get sent to slaughter ( $X_t$ ) will be retained for addition to the breeding stock in period  $t + 1$ .<sup>7</sup>

Using (6) as the empirical specification of  $f(S_t, X_t)$ , it is straightforward to apply the techniques in appendix A to derive the following first-order condition for beef-packing firms (see appendix B):

$$A_t = \sum_{k=1}^3 \beta^k \gamma_0^{k-1} R_t^i \left[ A_{t+k} \frac{dx_{t+k}^i}{dS_{t+k}} + N_{t+k} \frac{\partial x_{t+k}^j}{\partial S_{t+1}} - w_{S,t+k} x_{t+k}^i \right] \quad (7)$$

where  $A_t$  represents the marginal value of the last animal sent to slaughter in period  $t$ , and the right-hand side represents the marginal value of leaving the animal in the breeding herd. The intuition behind (7) is the same as for equation 1, but it is slightly more complex given the three-year lag structure for stock dynamics. As before, if packers are forward looking,  $\beta$  will not be equal to zero, and static market-power estimates from  $A_t = 0$  are likely to be biased.

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<sup>7</sup>This specification assumes that the cull rate for cows is constant over time. Clearly this is an abstraction from reality, but one that greatly simplifies our analysis. Furthermore, allowing ranchers to make endogenous culling decisions along only one margin (heifers in our model) is consistent with several leading studies of cattle supply (e.g., Rosen et al. (1994), Rosen (1987)).

### 3.2 Estimating Equations

To examine the direction and magnitude of the bias, we estimate four equations: (1) the retail demand for fed beef; (2) the input supply of fed heifers; (3) the packer's equilibrium first-order condition (equation 7) with  $\beta$  set to zero ( $A_t = 0$ ); and (4) equation 7 with  $\beta$  allowed to be greater than zero.

We begin by assuming that the demand for fed beef can be represented by a log-linear inverse demand function:

$$\ln(p_t) = b_0 + b_1 \ln(X_t) + b_2 \ln(di_t) + b_3 \ln(pc_t) + b_4 \ln(pp_t) + \varepsilon_{1,t}, \quad (8)$$

where  $p_t$  is the retail price of fed beef,  $di_t$  is disposable income,  $pc_t$  is the price of chicken,  $pp_t$  is the price of pork, and  $\varepsilon_{1,t}$  is an error term. We hypothesize that the demand curve is downward-sloping ( $b_1 < 0$ ), fed beef is a normal good ( $b_2 > 0$ ), and chicken and pork are substitutes for fed beef ( $b_3, b_4 > 0$ ).

The input supply of fed heifers is also assumed to be log-linear:

$$\ln(w_t) = c_0 + c_1 \ln(X_t) + c_2 \ln(S_t) + c_3 \ln(pcow_{t+1}^e) + c_4 \ln(pfeed_{t+1}^e) + \varepsilon_{2,t}. \quad (9)$$

Heifers have value both as consumption and capital goods. Their consumption value is derived from consumers' demand for fed beef (8) and their capital value is derived from their ability to produce calves. Therefore, we model the price of heifers ( $w_t$ ) as a function of the quantity supplied ( $X_t$ ), the stock of cows in the current period ( $S_t$ ), and their expected value as a cow in the following year ( $pcow_{t+1}^e$ ) net of holding costs ( $pfeed_{t+1}^e$ ).<sup>8</sup> To calculate future expected values, we use quasi-rational expectations as presented in Nerlove and Fornari (1998), which amounts to using the best-fitting time series model to forecast future values. For both cow and feed prices, we used integrated ARMA(1,1) time series models to generate forecasts.

Studies generally suggest that the short-run supply response for heifers is positive for transitory price shocks and negative for permanent price shocks (Jarvis (1974) and Rosen (1987)). Therefore, we hypothesize that the price of heifers could be (depending on the nature of the price shocks) either negatively or positively related to the quantity supplied ( $c_1 \geq 0$ ). Reductions in current stocks and expected feed prices, as well as increases in expected cow prices, should cause producers to retain

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<sup>8</sup>Note that the market value of a cow will automatically incorporate feed and cattle prices further into the future because the value of a cow equals the net discounted stream of revenues from her calves over her productive lifetime.

more heifers and therefore reduce the current quantity supplied to the market. Moving  $\ln(X)$  alone to the left-hand side of equation 9 then implies that the price of heifers should be negatively (positively) related to current stocks and expected feed prices and positively (negatively) related to expected cow prices if the slope of the supply curve is positive (negative).

The last econometric equation is derived from the equilibrium first-order condition for packers (equation 7). To derive this equation, we make several simplifying assumptions. First, since we have aggregate data, we assume symmetry in firm conjectures (although not necessarily across input usage or production costs). Second, we assume that  $d_1 (= dx_t^i/dS_t)$ ,  $d_2 (= \partial x_t^j/\partial S_t)$ ,  $c_t'$  and  $\theta_t^i$  (or equivalently  $R_t^i$ ) are constant for all  $t$ . In other words, we assume that marginal slaughter rates, marginal processing costs and (as in Roberts and Samuelson (1988)) the conjectural-elasticity parameter do not change over time.<sup>9</sup> Furthermore, since both demand and supply are assumed to be log-linear, we know that  $p'_{t+k} = b_1(p_{t+k}/X_{t+k})$ ,  $w_{X,t+k} = c_1(w_{t+k}/X_{t+k})$  and  $w_{S,t+k} = c_2(w_{t+k}/S_{t+k})$ .

In appendix C, we show that equation 7 can be rewritten as

$$(p_t - w_t) = a + \theta(c_1 w_t - b_1 p_t + c_2 \Gamma_{1,t}) + (d_1 \theta^2 + d_2 \theta \frac{x^i}{X}) \Gamma_{2,t} + d_1 \theta \Gamma_{3,t} + \varepsilon_{3,t} \quad (10)$$

where  $\theta$  is the conjectural elasticity parameter defined above;  $a$ ,  $d_1$ ,  $d_2$  and  $x^i/X$  are constant over time;  $\varepsilon_{3,t}$  is a stochastic error term; and the  $\Gamma$  terms involve future prices, slaughter and stocks.<sup>10</sup> Exclusion of  $\Gamma_{1,t}$ ,  $\Gamma_{2,t}$  and  $\Gamma_{3,t}$  from (10) produces the CV estimates derived from a static model of competition, which implicitly assumes that packer behavior is myopic. The primary goal of this paper is to determine whether estimates of  $\theta$  from models that exclude the  $\Gamma$  terms (or equivalently assume that  $\beta = 0$ ) are biased. That is, we are trying to discover whether aggregate stock dynamics matter in the market for live cattle.

We use U.S. aggregate time series data from 1933 to 1999 to estimate the model (details about the data are included in appendix D). Our stock variable ( $S$ ) is measured by the total number of cows that have calved as of January 1. Total slaughter ( $X$ ) is given by the total annual number of

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<sup>9</sup>To justify this assumption, we performed a test of parameter constancy by calculating recursive coefficients for equation (7). That is, we begin with the sample period 1933-1963 and sequentially add a single observation to the end of the sample until reaching 1999 – each time calculating an updated set of coefficients. These recursive coefficients shows little evidence of a structural break. Due to space limitations, these results are not shown here but are available upon request.

<sup>10</sup>It is difficult to separate the DDE and IDE in our empirical specification. However, because  $d_1$  gives firm  $i$ 's reaction to changes in future period stocks, it is related to the DDE. Since  $d_2$  gives firm  $j$ 's reaction to changes in future periods, it is related to the IDE. The packers' consideration of rancher cull decisions in response to changes in stocks is contained in  $\Gamma_1$ .

federally inspected slaughtered heifers. The prices for heifers ( $w$ ) and cull cows ( $pcow$ ) are given by the USDA-reported market price at Chicago prior to 1968 and by the market price at Omaha thereafter.<sup>11</sup> Output prices ( $p$ ) are given by the average wholesale prices of commercial dressed heifer and steer beef from 1933 through 1988. After 1988 the USDA stopped reporting wholesale prices for dressed carcasses because packing firms had begun to process carcasses into primal cuts and sell them in boxes. For 1989-1999, we use the wholesale boxed-beef price. The final four series are the price of broiler chickens ( $pc$ ), the price received by farmers for hogs ( $pp$ ), the price of feed index ( $pfeed$ ), and U.S. disposable income ( $di$ ). All nominal series are deflated by the U.S. consumer price index.

### 3.3 Results

Our estimation is completed in two stages. In stage one, we jointly estimate equations 8 and 9. Then in stage two, conditional on these estimated elasticities, we estimate the CV elasticity  $\theta$  in (10) for two cases: (i) with myopic packer behavior and (ii) with forward-looking packer behavior.<sup>12</sup>

Equations 8 and 9 are estimated using three-stage least squares (3SLS) because of the potential endogeneity associated with  $\ln(X)$  and  $\ln(S)$ . The set of instruments include the remaining exogenous variables in the system as well as once-lagged  $\ln(S)$ . The estimates for (10) are generated with an autocorrelation-corrected instrumental-variable technique. The set of instruments for (10) are the same as in the 3SLS estimation plus the first three lags of  $w_t$  and  $p_t$ . The results are presented in table 1.

[Insert table 1 here]

Begin by focusing on the results in the first two columns of table 1. The primary coefficients of interest in the estimation of equations (8) and (9) are the price elasticities with respect to slaughter and stocks. Since we estimated log-linear inverse demand and supply functions, the reciprocal of  $b_1$  gives the price elasticity of demand and the reciprocals of  $c_1$  and  $c_2$  give the price elasticities of

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<sup>11</sup>The heifer price series begins in 1964. Prior to 1964, we use the price of steers as our measure of  $\omega$  and include an input-price dummy variable (one after 1963; zero otherwise) to control for the break in the series. For the period after 1963, where both the price of heifers and steers are available, the two prices follow one another very closely with a correlation coefficient equal to 0.99945.

<sup>12</sup>Ideally, the myopic and forward-looking first-order conditions for the packers would each be estimated in a system (imposing the appropriate cross-equation restrictions) along with the input supply and retail demand functions. However, given the nature of the optimizing equation for the packers, we found that both full maximum likelihood and generalized method of moments estimation tend to generate unreasonable demand and supply elasticities. We therefore rely on estimates from the two-stage procedure.

supply with respect to slaughter and stocks. The estimated inverse demand elasticity suggests that demand for fed beef is elastic with respect to its price (i.e., an elasticity of  $(-0.618)^{-1} = -1.618$ ) and is statistically significant at the 1% level. The magnitude of this estimate is consistent with the empirical literature on the responsiveness of the demand for fed beef to changes in its price (Smallwood, Haidacher and Blaylock (1989)). The coefficient for the supply elasticity with respect to slaughter is positive and statistically significant at the 1% level. This is consistent with the theoretical arguments of Aadland and Bailey (2001) that the short-run supply response to transitory *and permanent* price changes in fed beef are generally positive. The sign on  $\ln(S)$  also makes sense as it implies that ranchers reduce cull rates in response to lower inventories. Finally, the signs on the other variables in (8) and (9) generally agree with our expectations, with the exception of the coefficient on the price of chicken ( $pc$ ) and expected feed prices ( $pfeed^e$ ).

The final two columns in table 1 report the conjectural elasticity estimates for myopic and forward-looking packers.<sup>13</sup> We wish to highlight two important features of these behavioral estimates for beef-packing firms. First, the coefficient estimates associated with forward-looking terms  $\Gamma_2$  and  $\Gamma_3$  are statistically significant at the 1% level. This suggests that beef-packing firms are indeed forward-looking and consider dynamic inventory constraints when making purchasing decisions. Second, the myopic estimate of the conjectural elasticity parameter ( $\theta = 0.347$ ) is substantially larger than the forward-looking estimates ( $\theta = 0.189$ ).<sup>14</sup> This shows that myopic CV estimates are upwardly biased and implies that packers are not exerting as much market power as the myopic estimates would suggest.<sup>15</sup>

The result that myopic market-power measures tend to overstate the amount of market power being exerted is intuitive. Consider, for example, a temporary increase in the demand for beef at the retail level. The positive demand shock will place upward pressure on the retail price of beef. To the extent that packers have market power on the output side, they will simultaneously raise prices and produce more boxed beef to meet the higher demand for their product. On the input

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<sup>13</sup>The results in the last column of table 1 are conditioned upon the following parameter values for cattle stock dynamics:  $\beta = 0.96$ ,  $\gamma = 0.85$ ,  $\delta = 0.1$ ,  $(X/x) = 3$  and  $\alpha = 0.2$ . We experimented with other reasonable values for these parameters and found the qualitative differences between the myopic and forward-looking estimates of  $\theta$  to be robust to these changes.

<sup>14</sup>The myopic estimates are comparable to those of many studies of market power in beef packing. See for example Bhuyan and Lopez (1997), Azzam (1997), and Schroeter and Azzam (1990).

<sup>15</sup>As a matter of clarification, since we are arguing that myopic estimates of market power are biased, it is not strictly valid to discuss their degree of statistical significance because their standard errors are also likely to be biased. That said, using the estimated standard errors for the two cases, we would reject the null that the myopic and forward-looking conjectural elasticities are equal, even assuming a zero covariance between the two estimates. Any positive covariance between estimators (which is likely given the nature of the estimators) would make rejection of the null hypothesis even stronger.

side, packers are not likely to completely pass the higher prices on to cattle producers because of market power and intertemporal stock concerns. In a myopic model, this action by packers and the resultant higher market power measure ( $\mathcal{M}$ ) will be perceived as a reflection of their market power. In a model that controls for dynamic stock constraints, it is explicitly recognized that packers are also concerned about future availability of fed-cattle inputs. By raising input prices too high in the current period, they will reduce the future breeding stock of cows and thus will be required to offer higher future input prices to meet retail demand. To avoid this scenario, packers will optimally choose not to pass all of the higher retail price for beef on to cattle producers, at least in part because of dynamic inventory constraints. Static models wrongly attribute all of the increased price-cost margins to the market power of packers, while dynamic models do not.

## 4 Conclusion

Standard measures of market power are derived from models in which firms are assumed to maximize profits period by period without concern for inventory dynamics. However, if inputs can be produced only with some lag, firms are likely to account for the effect of their current choices on input availability in the future. We present a model which incorporates this intertemporal link. Our model gives an exact characterization of the bias that is created when the standard (static) framework is applied to an inherently dynamic problem. While the bias does not disappear even in the steady state, it cannot be theoretically signed.

To examine the issue further, we apply this model to the beef-packing industry, using aggregate data from 1933 through 1999. This industry provides a good test of the model, as increased concentration in beef-packing continues to be a major policy issue in the United States, although most previous studies of market power in beef packing ignore the intertemporal considerations necessitated by stock dynamics.

We find that myopic market-power measures tend to overstate the degree of packer market power. Consistent with many theoretical models, we find that consideration of future periods appears to constrain the firm's ability to exercise current market power. Thus, we provide an interesting extension to many previous tests of market power in beef packing. Our results support the conclusion that packers appear to have limited ability to reduce the prices they pay for fed cattle. Given that controlling for intertemporal considerations reduces the market-power measure by nearly 50%, we find even further support for the claim that packers do not exercise market power through their input prices. Whether this result is robust to alternative, and perhaps less

aggregated, data sets remains an open question.

## A Derivation of Theoretical Market-Power Measures

The firm chooses  $x^i$  in each period to maximize its discounted profit stream:

$$\max_{\{x^i\}} \sum_{t=0}^{\infty} \beta^t [\{p(X_t) - w(X_t, S_t)\} x_t^i - c(x_t^i)]$$

subject to  $S_{t+1} = f(S_t, X_t)$  and  $S_0$  given.

There are two terms of interest. Dividing through by  $\beta^t$ , they are

$$\{p(X_t) - w(X_t, S_t)\} x_t^i - c(x_t^i) + \beta [\{p(X_{t+1}) - w(X_{t+1}, S_{t+1})\} x_{t+1}^i - c(x_{t+1}^i)]$$

Noting the dependence of variables on  $X_t$  and  $S_t$ , and taking the derivative of this equation with respect to  $x_t^i$  and setting it to zero gives

$$0 = \{p_t - w_t - c'_t\} + \{p'_t - w_{X,t}\} x_t^i R_t^i$$

$$+ \beta \left[ \{p_{t+1} - w_{t+1} - c'_{t+1}\} \frac{dx_{t+1}^i}{dx_t^i} \right] + \beta \left[ \{p'_{t+1} - w_{X,t+1}\} x_{t+1}^i \frac{dX_{t+1}}{dx_t^i} - w_{S,t+1} x_{t+1}^i \frac{dS_{t+1}}{dx_t^i} \right]$$

where  $p_t \equiv p(X_t)$ ,  $p'_t \equiv p'(X_t)$ , and similarly for  $w$  and all variables subscripted with  $t+1$ . Now we need to find expressions for  $dx_{t+1}^i/dx_t^i$ ,  $dS_{t+1}/dx_t^i$  and  $dX_{t+1}/dx_t^i$ . The first two can be calculated as follows

$$\frac{dx_{t+1}^i}{dx_t^i} = \frac{dx_{t+1}^i}{dS_{t+1}} \frac{dS_{t+1}}{dx_t^i} = \frac{dx_{t+1}^i}{dS_{t+1}} \left( \frac{dS_{t+1}}{dX_t} \frac{dX_t}{dx_t^i} \right) = \frac{dx_{t+1}^i}{dS_{t+1}} (f_X R_t^i)$$

Next, we must calculate  $dX_{t+1}/dx_t^i$ . Recall that  $X_{t+1} = x_{t+1}^i(S_{t+1}) + x_{t+1}^j(x_{t+1}^i(S_{t+1}), S_{t+1})$ . This implies that

$$\begin{aligned}
\frac{dX_{t+1}}{dx_t^i} &= \frac{dx_{t+1}^i}{dx_t^i} \left( 1 + \frac{dx_{t+1}^j}{dx_{t+1}^i} \right) + \frac{\partial x_{t+1}^j}{\partial S_{t+1}} \frac{dS_{t+1}}{dx_t^i} \\
&= \frac{dx_{t+1}^i}{dx_t^i} R_{t+1}^i + \frac{\partial x_{t+1}^j}{\partial S_{t+1}} \frac{dS_{t+1}}{dx_t^i} \\
&= \frac{dx_{t+1}^i}{dS_{t+1}} f_X R_t^i R_{t+1}^i + \frac{\partial x_{t+1}^j}{\partial S_{t+1}} f_X R_t^i \\
&= f_X R_t^i \left[ \frac{dx_{t+1}^i}{dS_{t+1}} R_{t+1}^i + \frac{\partial x_{t+1}^j}{\partial S_{t+1}} \right].
\end{aligned}$$

Plugging these three values into the first-order condition, we obtain

$$\begin{aligned}
0 &= \{p_t - w_t - c_t'\} + \{p_t' - w_{X,t}\} x_t^i R_t^i \\
&\quad + \beta \{p_{t+1} - w_{t+1} - c_{t+1}'\} \frac{dx_{t+1}^i}{dS_{t+1}} f_X R_t^i \\
&\quad + \beta \left[ \{p_{t+1}' - w_{X,t+1}\} x_{t+1}^i f_X R_t^i \left[ \frac{dx_{t+1}^i}{dS_{t+1}} R_{t+1}^i + \frac{\partial x_{t+1}^j}{\partial S_{t+1}} \right] - w_{S,t+1} x_{t+1}^i f_X R_t^i \right] \\
&= A_t - p_t \Delta.
\end{aligned}$$

We define  $A_t = \{p_t - w_t - c_t'\} + \{p_t' - w_{X,t}\} x_t^i R_t^i$ ,  $N_{t+1} = \{p_{t+1}' - w_{X,t+1}\} x_{t+1}^i$   
and  $\Delta = -(\beta f_X R_t^i / p_t) [A_{t+1} (dx_{t+1}^i / dS_{t+1}) + N_{t+1} (\partial x_{t+1}^j / \partial S_{t+1}) - w_{S,t+1} x_{t+1}^i]$ .

From the previous equation, the (closed-loop) price-cost margin can be written as

$$\begin{aligned}
\mathcal{L}_t^c &= \frac{p_t - w_t - w_{X,t} x_t^i R_t^i - c_t'}{p_t} \\
&= -\frac{p_t'}{p_t} x_t^i R_t^i + \Delta = -\frac{\theta_t^i}{\varepsilon_t} + \Delta.
\end{aligned}$$

Let  $\mathcal{M}^c$  denote the measure of oligopsony power, which is given by the difference between net marginal revenue product and the input price, normalized by the input price. Manipulating the

first-order equation, we obtain

$$\begin{aligned}
\mathcal{M}_t^c &= \frac{p_t - w_t + p'_t x_t^i R_t^i - c'_t}{w_t} \\
&= \frac{w_{X,t} x_t^i R_t^i}{w_t} - \frac{\beta f_X R_t^i}{w_t} \left[ A_{t+1} \frac{dx_{t+1}^i}{dS_{t+1}} + N_{t+1} \frac{\partial x_{t+1}^j}{\partial S_{t+1}} - w_{S,t+1} x_{t+1}^i \right] \\
&= \frac{\theta_t^i}{\eta_t} + \Gamma
\end{aligned}$$

where  $\Gamma = -(\beta f_X R_t^i / w_t) [A_{t+1} (dx_{t+1}^i / dS_{t+1}) + N_{t+1} (\partial x_{t+1}^j / \partial S_{t+1}) - w_{S,t+1} x_{t+1}^i]$ .

## B Derivation of the Empirical Market-Power Measures

As before, the firm's problem is

$$\begin{aligned}
&\max_{\{x^i\}} \sum_{t=0}^{\infty} \beta^t [\{p(X_t) - w(X_t, S_t)\} x_t^i - c(x_t^i)] \\
&\text{subject to } S_{t+1} = \gamma_0 S_t + \gamma_2 S_{t-2} - X_t \text{ and } S_0 \text{ given.}
\end{aligned}$$

There are four terms of interest from this discounted stream of profits:

$$\begin{aligned}
&\beta^t [\{p(X_t) - w(X_t, S_t)\} x_t^i - c(x_t^i)] \\
&+ \beta^{t+1} [\{p(X_{t+1}) - w(X_{t+1}, S_{t+1})\} x_{t+1}^i - c(x_{t+1}^i)] \\
&+ \beta^{t+2} [\{p(X_{t+2}) - w(X_{t+2}, S_{t+2})\} x_{t+2}^i - c(x_{t+2}^i)] \\
&+ \beta^{t+3} [\{p(X_{t+3}) - w(X_{t+3}, S_{t+3})\} x_{t+3}^i - c(x_{t+3}^i)].
\end{aligned}$$

Dividing through by  $\beta^t$ , noting the dependence of variables on  $X_{t+k}$  and  $S_{t+k}$  for  $k = 1, 2, 3$ , taking the derivative with respect to  $x_t^i$ , and setting the derivative equal to zero gives

$$\sum_{k=0}^3 \beta^k \left[ \{p_{t+k} - w_{t+k} - c'_{t+k}\} \frac{dx_{t+k}^i}{dx_t^i} + \{p'_{t+k} - w_{X,t+k}\} x_{t+k}^i \frac{dX_{t+k}}{dx_t^i} - w_{S,t+k} x_{t+k}^i \frac{dS_{t+k}}{dx_t^i} \right] = 0$$

where  $dS_t/dx_t^i = 0$ .

This equation can be rewritten as

$$0 = p_t - w_t - c'(x_t^i) + \{p'_t - w_{X,t}\} x_t^i R_t^i + \sum_{k=1}^3 \beta^k \left[ \{p_{t+k} - w_{t+k} - c'(x_{t+k}^i)\} \frac{dx_{t+k}^i}{dx_t^i} + \{p'_{t+k} - w_{X,t+k}\} x_{t+k}^i R_{t+k}^i - w_{S,t+k} x_{t+k}^i \frac{dS_{t+k}}{dx_t^i} \right].$$

Recall that from the stock dynamics equation  $dS_{t+1}/dX_t = -1$ . As in appendix A, we need to calculate  $dx_{t+k}^i/dx_t^i$ ,  $dS_{t+k}/dx_t^i$  and  $dX_{t+k}/dx_t^i$ .

The first two derivatives can be written as:

$$\frac{dx_{t+k}^i}{dx_t^i} = \frac{dx_{t+k}^i}{dS_{t+k}} \frac{dS_{t+k}}{dx_t^i} = \frac{dx_{t+k}^i}{dS_{t+k}} \left( \frac{dS_{t+k}}{dS_{t+1}} \frac{dS_{t+1}}{dX_t} \frac{dX_t}{dx_t^i} \right) = -\frac{dx_{t+k}^i}{dS_{t+k}} \left( \frac{dS_{t+k}}{dS_{t+1}} R_t^i \right).$$

To calculate the third derivative, recall that  $X_{t+k} = x_{t+k}^i(S_{t+k}) + x_{t+k}^j(x_{t+k}^i(S_{t+k}), S_{t+k})$ . Taking the derivative with respect to  $x_{t+k}^i$  gives

$$\begin{aligned} \frac{dX_{t+k}}{dx_t^i} &= \frac{dx_{t+k}^i}{dx_t^i} \left( 1 + \frac{dx_{t+k}^j}{dx_{t+k}^i} \right) + \frac{\partial x_{t+k}^j}{\partial S_{t+k}} \frac{dS_{t+k}}{dx_t^i} \\ &= -\frac{dx_{t+k}^i}{dS_{t+k}} \frac{dS_{t+k}}{dS_{t+1}} R_t^i \left( 1 + \frac{dx_{t+k}^j}{dx_{t+k}^i} \right) - \frac{\partial x_{t+k}^j}{\partial S_{t+k}} \frac{dS_{t+k}}{dS_{t+1}} R_t^i \\ &= -R_t^i \frac{dS_{t+k}}{dS_{t+1}} \left[ \frac{dx_{t+k}^i}{dS_{t+k}} R_{t+k}^i + \frac{\partial x_{t+k}^j}{\partial S_{t+k}} \right]. \end{aligned}$$

By the dynamic stock constraint above,  $dS_{t+2}/dS_{t+1} = \gamma_0$  and  $dS_{t+3}/dS_{t+1} = \gamma_0^2$ .

Substituting all these terms into the first-order condition for firm  $i$ , and defining  $A$  and  $N$  as in appendix A above, gives:

$$\begin{aligned} A_t &= \beta R_t^i \left[ A_{t+1} \frac{dx_{t+1}^i}{dS_{t+1}} + N_{t+1} \frac{\partial x_{t+1}^j}{\partial S_{t+1}} - w_{S,t+1} x_{t+1}^i \right] \\ &\quad + \beta^2 \gamma_0 R_t^i \left[ A_{t+2} \frac{dx_{t+2}^i}{dS_{t+2}} + N_{t+2} \frac{\partial x_{t+2}^j}{\partial S_{t+2}} - w_{S,t+2} x_{t+2}^i \right] \\ &\quad + \beta^3 \gamma_0^2 R_t^i \left[ A_{t+3} \frac{dx_{t+3}^i}{dS_{t+3}} + N_{t+3} \frac{\partial x_{t+3}^j}{\partial S_{t+3}} - w_{S,t+3} x_{t+3}^i \right]. \end{aligned}$$

Translating to summation notation leads to equation (7).

## C Derivation of the Estimating Equation

We define  $d_1 = (dx_t^i/dS_t)$ ,  $d_2 = (\partial x_t^i/\partial S_t)$ , and assume that  $c_t'$  is constant over time, and  $\theta_t^i$  is constant across firms and over time. Recall that our log-linear demand and supply equations give  $p_{t+k}' = b_1(p_{t+k}/X_{t+k})$ ,  $w_{X,t+k} = c_1(w_{t+k}/X_{t+k})$  and  $w_{S,t+k} = c_2(w_{t+k}/S_{t+k})$ . Equation (7) then simplifies to

$$(p_t - w_t) = a + \theta(c_1 w_t - b_1 p_t + c_2 \Gamma_{1,t}) + (d_1 \theta^2 + d_2 \theta \frac{x^i}{X}) \Gamma_{2,t} + d_1 \theta \Gamma_{3,t} + \varepsilon_{3,t}$$

where  $\theta$  is the conjectural elasticity parameter defined above;  $a = c'[1 - d_1 \theta (X/x^i)(\beta + \beta^2 \gamma_0 + \beta^3 \gamma_0^2)]$ ,  $d_1$  and  $d_2$  are assumed to be constant over time;  $\varepsilon_{3,t}$  is an added stochastic error term; and

$$\begin{aligned} \Gamma_{1,t} &= -(X_t/x_t^i) \left\{ \begin{array}{l} \beta[w_{t+1}(x_{t+1}^i/S_{t+1})] + \beta^2 \gamma_0[w_{t+2}(x_{t+2}^i/S_{t+2})] + \\ \beta^3 \gamma_0^2[w_{t+3}(x_{t+3}^i/S_{t+3})] \end{array} \right\} \\ \Gamma_{2,t} &= -(X_t/x_t^i) \left\{ \begin{array}{l} \beta[c_1 w_{t+1} - b_1 p_{t+1}] + \beta^2 \gamma_0[c_1 w_{t+2} - b_1 p_{t+2}] + \\ \beta^3 \gamma_0^2[c_1 w_{t+3} - b_1 p_{t+3}] \end{array} \right\} \\ \Gamma_{3,t} &= -(X_t/x_t^i) \left\{ \begin{array}{l} \beta[w_{t+1} - p_{t+1}] + \beta^2 \gamma_0[w_{t+2} - p_{t+2}] + \\ \beta^3 \gamma_0^2[w_{t+3} - p_{t+3}] \end{array} \right\}. \end{aligned}$$

## D Data Appendix

Unless otherwise stated, the data are taken from *Agricultural Statistics*, an annual publication of the USDA. The table numbers in *Agricultural Statistics* vary over time, so only table numbers for select years are shown. Our stock variable ( $S$ ) is measured by the number of cows and heifers that have calved as of January 1 in the U.S. (Table 7-2, 1999). Total slaughter ( $X$ ) is given by the total annual number of federally inspected slaughtered heifers in the U.S., including imported live animals (Table 7-18, 1999). Prices per 100 pounds for choice fed heifers ( $w$ ) and commercial cull cows ( $pcow$ ) are, prior to 1968, given by the market price at Chicago and after 1968, are given by the market price paid to farmers at Omaha (Table 7-9, 1999). Since the price of heifers series begins in 1964, we substitute the price of choice steers prior to 1964. Output prices ( $p$ ) are given by the average wholesale price per 100 pounds for select commercial dressed heifers and steers (600-700 lb.) from 1933 through 1988 (Table 401, 1989). For 1989-1999, we use the central U.S. wholesale price for dressed boxed-beef cut-out obtained from the Livestock, Meat & Wool Division of the Agricultural Marketing Service, USDA. The final three agricultural series are the U.S. price

of broiler chickens per pound ( $pc$ ) (Table 8-45, 1999), the average U.S. price received by farmers for hogs per pound ( $pp$ ) (Table 7-33, 1999), and the U.S. price of feed index ( $pfeed$ ) (1992-4 = 100) (Table 9-33, 1999). U.S. nominal disposable income ( $di$ ) is obtained from the *NBER Macroeconomic Database* (<http://www.nber.org/databases/macroeconomic/contents/>) for the period 1933-1946 and from the *Federal Reserve Economic Database* (FRED; <http://www.stls.frb.org/fred/index.html>) after 1946. The U.S. consumer price index for all goods and services (1967 = 100), which is used to deflate all nominal prices, is obtained from the *Bureau of Labor Statistics* (<http://stats.bls.gov/>).

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Table 1. Instrumental Variables Estimation Results (Annual Data 1933 - 1999)

| Explanatory Variables  | Dependent Variables  |                       |                     |                     |
|--|----------------------|-----------------------|---------------------|---------------------|
|  | ln(w)                | ln(p)                 | (p-w)               | (p-w)               |
| Constant   | 6.445*<br>(1.848)    | -0.432<br>(-1.283)    | 0.016<br>(0.797)    | -0.023<br>(-1.040)  |
| ln(X)  | 0.547***<br>(2.600)  | -0.618***<br>(-4.226) |                     |                     |
| ln(di)   |                      | 0.209<br>(1.382)      |                     |                     |
| ln(pc)   |                      | -0.605***<br>(-3.575) |                     |                     |
| ln(pp)   |                      | 0.703***<br>(6.719)   |                     |                     |
| ln(S)  | -2.195**<br>(-2.025) |                       |                     |                     |
| ln(pcow) forecast  | 0.547***<br>(7.900)  |                       |                     |                     |
| ln(pfeed) forecast   | 1.025***<br>(2.736)  |                       |                     |                     |
| (c <sub>1</sub> w - b <sub>1</sub> p)                                  |                      |                       | 0.347***<br>(7.357) |                     |
| (c <sub>1</sub> w - b <sub>1</sub> p + c <sub>2</sub> Γ <sub>1</sub> ) |                      |                       |                     | 0.189***<br>(3.214) |
| Γ <sub>2</sub>   |                      |                       |                     | 0.048***<br>(2.849) |
| Γ <sub>3</sub>   |                      |                       |                     | 0.204***<br>(8.149) |

Notes: *t* statistics are in parentheses. (\*\*\*), (\*\*), and (\*) refer to statistical significance at the 1, 5 and 10 percent levels respectively. The coefficients for the box-beef dummy (unity after 1988; zero otherwise) and the input-price dummy (unity after 1963; zero otherwise) are excluded.