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The Long Run and Short Run Impact of Captive Supplies on the Spot Market Price: An Agent-Based Artificial Market

This paper seeks to reduce the gap between theoretical research that shows a potentially large price-depressing effect of captive supplies and empirical work that finds any price-depressing effect of captive supplies is small. An agent-based model is developed that matches the results of Xia and Sexton (2004) as well as our generalization of their model. We relax Xia and Sexton's (2004) assumption of no supply response by captive feeders, which reduces the price depressing effect of captive supplies. Finally, the agent-based model is used to simulate packers choosing both captive supply quantities and spot market quantities. Packers in the relaxed agent-based model choose no captive supplies and thus reach the Cournot solution. The research narrows the gap between theoretical models and the empirical work on captive supplies that shows little effect on prices, but a gap remains.

Key words: Agent-based market, captive supplies, cattle, industrial organization, particle swarm optimization

Introduction

In the beef packing industry, vertical integration through captive supplies between packers and feeders has been a divisive issue for more than 20 years (Ward 2009). Captive supplies include marketing agreements, packer owned cattle, and forward contracts. Most packers procure cattle both through exclusive captive supply contracts and from the spot market. According to a recent GIPSA Livestock and Meat Marketing Study (Muth et al. 2007; Muth et al. 2008), 38.3% of cattle were purchased with captive supplies, from which marketing agreements take the largest share of 28.8%, with 4.5% forward contracted, and the rest packer owned. Ward (2009) reports that 46.3% of fed cattle were captive supplies in 2008. The price of captive supply cattle is typically linked to the subsequent spot market price. In addition to increased vertical integration, the U.S. beef processing industry also experienced horizontal integration with the four-firm concentration ratio reaching 80% in 2002 (Ward 2002).

The increased use of captive supplies by oligopsony packing firms has led to concern about negative impacts of captive supplies on cattle prices (e.g. Azzam 1998; Connor et al. 2002). Xia and Sexton (2004) construct a theoretical duopsony market where packers purchase cattle both with exclusive captive contracts and in the spot market, and the price of captive supplies is linked to the spot market price. They show that packers can use captive supplies to reduce competition and depress price to the monopsony level if 50% of the cattle are contracted. In contrast to the large price depression predicted by Xia and Sexton's theoretical model, previous empirical studies have found that captive supplies have only a small negative or insignificant effect. Ward, Koontz and Schroeder (1998) find small negative relationships between price and the percentage of cattle delivered with forward contracts and marketing agreements. Parcell, Schroeder, and Dhuyvetter (1997) find that captive supply shipments have no economically or statistically significant effect on live cattle basis. Muth et al. (2007)

gives similar results as the previous empirical studies and shows that a 10% increase in capacity utilization through captive supplies is associated with a small price decrease of $0.04 per pound of carcass weight.

One possible explanation of the difference between Xia and Sexton's static model and the previous empirical results is that price depression from captive supplies is a short run effect. In the long run, if packers reduce the price they pay for cattle, contracted feeders[1] will reduce the number of cattle they produce.

We use agent-based computational economics (ACE) to study the fed cattle market by conducting experiments with simulated agents. Agent-based computational economics (ACE) simulates games between interactive agents (Tesfatsion 2001, 2006) and adopts concepts and methods from game theory, cognitive science and computer science. An agent-based model is a computer simulation model of autonomous entities called agents. These artificial agents follow relatively simple rules. The rules have parameters and the agents learn by choosing parameters that worked well in past iterations of the simulation.

ACE has been used to study the behavior of agents in the cobweb model, the exchange rate problem, prisoner's dilemma, etc. (Arifovic 1996; Axelrod 1987; Riechmann 2001; Vriend 2000). Recent work with Cournot oligopoly models, finds that agents in agent-based models can find the Cournot oligopoly solution, but results depend on the learning rule used (Waltman and Kaymak 2008; Kimbrough and Murphy 2009; Qiao and Rozenblit 2009; Anderson and Cau 2009). Within agricultural economics, the use of agent-based models has been largely limited to land-use planning (Balmann 1997; Berger 2001; Matthews 2007). ACE can be used to study problems with behavioral assumptions that are too difficult to analyze with mathematical methods. ACE is more economical and time efficient compared to experiments with human subjects (eg. Ward et al. 1999) and it is more controllable.

This research uses a particle swarm optimization (PSO) algorithm to model the learning behavior of packers in the artificial fed cattle market. PSO is a stochastic optimization technique developed by Eberhart and Kennedy (1995). The idea of PSO came from observing how flocks of birds, fish, or other animals adapt to avoid predators or to find food by sharing information. In our game, packers do not cooperate with each other and only learn from their own experience. Thus, we adjust PSO by constructing multiple parallel markets and letting each packer have its own packing plant in every market. Packers trade in every market simultaneously and independently, but they learn only from their own experience. This means each packer has a separate "flock of birds" that does not share information with the flocks of the other packers.

We first expand Xia and Sexton's (2004) analytical model from the duopsonay case to the more general oligopsony case. Next, we extend Xia and Sexton (2004) to the long run where there is a supply response by feeders. Adding a supply response reduces

[1] In actual cattle markets, the drop in price will be passed on to cow-calf producers who will decrease production. Our model does not separate the cow-calf and feedlot sectors.

the price depressing effect of captive supplies, but does not remove it. We then develop an artificial fed cattle market using an agent-based model and use it to determine the impacts of captive supplies under different short run and long run contract assumptions. The agent-based model is verified since it gets the same solution as the short-run model of Xia and Sexton (2004) as well as matches our extension to the long run. We then use the agent-based model to study a problem that has so far proven too complex to solve analytically where packers choose both the quantity of captive supplies and the quantity to purchase in the open market.

The Oligopsony Market with Captive Supplies

Consider a homogeneous product market with M packers and N feeders. The number of packers is much less than the number of feeders ($M << N$). Packers procure from feeders and sell processed goods to the retail market. To focus our research on the game between packers and feeders in this market, we assume that the final processed boxed beef price, the processing rate, and the marginal cost are constant, so the fed cattle value to packers is also constant. This result means the marginal revenue for each animal is constant, and we define the marginal revenue as R. The assumption of a perfectly elastic output market is necessary so that packers have only oligopsony power and no oligopoly power.

Packers contract with feeders and then compete for the remaining cattle in the spot market. We follow Xia and Sexton's (2004) assumption that packers choose quantity rather than price. The market prices are determined by packers' total demand in the spot market and the aggregate supply from noncontracted feeders. We construct three scenarios by first fixing both the number of contracts and the quantity per contract. Next, we allow supply response by the contracted feeders. Finally, we allow supply response and let packers choose the number of captive supply contracts.

Fixed Number of Contracts and Fixed Quantity per Contract

Xia and Sexton (2004) only consider the duopsony case, but we generalize their results to the oligopsony case of M packers. Assume M processing packers and N feeders in the fed cattle market. Packers purchase cattle from feeders both with exclusive contracts and in the spot market. The price of contracted cattle is linked to the spot market price. Packers choose quantities rather than price and so this is a Cournot game.

Assume packers make exclusive contracts with n_i^c chosen feeders, and the quantity of each contract q_i^c is fixed, where c indicates contract market. In each period, the contracted feeders deliver cattle to packers and packers compete with each other for cattle from the non-contracted feeders. The spot price is determined by the market clearing price from the spot market aggregate demand and supply, and the contracted cattle are also valued with this price. Feeders always accept the contracts. We use S to indicate the total number of feeders with contracts, $S = \sum_{i=1}^{M} n_i^c$ and $S < N$.

At the beginning of each processing period, packers select their procurement strategies and then purchase cattle in the spot market. The choice variable of the procurement strategy is the procurement ratio:

$$x_{i,t}^{d} = q_{i,t}^{d} /(R \times N), \quad (1)$$

where $x_{i,t}^{d}$ is the procurement ratio, N is the total number of feeders, and the superscript d indicates packer's demand in the spot market. Packer i's processing quantity q_i^d is also the amount of its procurement. R is the marginal revenue of one packer and also the supply level of feeders under the perfect competition price level. For example, if under perfect competition, feeders provide 10,000 cattle and the processing quantity of packer i is 3,000, its procurement ratio x_i equals 0.3.

The total demand in the spot market can be written as $Q_t^d = \sum_{i=1}^{M} q_{i,t}^{d}$. We assume all feeders are homogeneous and have a linear supply function $q_{j,t}^{s} = p_t$, so the total supply in the spot market is $Q_t^s = (N-S)\,p_t$, since the S contracted feeders have no supply response. The market clearing condition is where the spot market aggregate demand equals supply, which is $Q_t^s = Q_t^d$. Thus, we obtain the equilibrium spot market price:

$$p_t = Q_t^d \big/ (N-S). \quad (2)$$

Packer i's total profit, which is determined by the quantity it purchases both with captive contracts and in the spot market, is $\pi_{i,t} = (R - p_t)(q_{i,t}^{d} + n_i q^c)$, $i = 1,\ldots,M$. Because the quantity per contract is fixed, the contract quantity $n_i q^c$ is constant for each processing period. Thus in every period, packers only need to decide how many cattle to buy through the spot market to maximize their profit. In addition, since packers' procurement decisions also affect the spot market price, we substitute equation (2) into the packers' profit function and solve its first order conditions with respect to $q_{i,t}^{d}$, holding $n_i q^c$ fixed to get the following packers' reaction functions:

$$q_{i,t}^{d} = R(N-S)/2 - \sum_{i' \neq i} q_{i',t}^{d} /2 - n_i^c q^c /2, \text{ for all } i = 1,\ldots,M. \quad (3)$$

Simultaneously solving these reaction functions of M packers, we obtain the spot demand quantities for each packer:

$$q_{i,t}^{d} = R(N-S)/(M+1) + (S - n_i^c) q^c /(M+1) - n_i^c q^c M /(M+1), \text{ for } i = 1,\ldots,M. \quad (4)$$

Add the above individual spot demands together and substitute the aggregate spot market demand $Q_t^d = \sum_{i=1}^{M} q_{i,t}^{d}$ into equation (2), and the spot market clearing price is

(5) $$p_t = MR/(M+1) - Sq^c/[(M+1)(N-S)].$$

From this result, we can see that without captive supplies, which means $S = 0$, the equilibrium price is the Cournot oligopsony level. With captive supplies, the price is lower than without them.

Now we assume the contracted feeder does not have a supply response and quantity q^c is fixed. We assume that the fixed quantity per contract will be based on the long run equilibrium price. Thus, packers and contracted feeders fix the quantity of a captive contract to Ep. Substitute $q^c = Ep$ to equation (5), which gives:

(6) $$Ep = M(N-S)R/[(M+1)N - MS].$$

If the oligopsony model is restricted to be a duopsony model by setting $M = 2$, this spot market price becomes $Ep = 2(N-S)R/(3N-2S)$, which is the same as equation (5') in Xia and Sexton (2004). In addition, when $(M-1)N/M$ feeders sign captive contracts and agree to produce at the market price level, the spot market price reaches the monopsony level $R/2$. For example, when there are $M = 4$ packers in the market, they need to make exclusive contracts with $3N/4$ feeders to depress the spot market to the monopsony level. In Xia and Sexton's duopsony model, packers only need to contract with $S = N/2$ feeders to depress the spot market price to the monopsony level. These results illustrate that the larger the number of packers, the larger number of aggregate exclusive contracts are needed to depress the spot market price the same amount. From the above results, we can see that the spot market price could be depressed to the monopsony level, when both the number of contracts and the quantity per contract are fixed.

Fixed Number of Contracts and Flexible Quantity per Contract

Now relax the previous model by allowing a supply response from contracted feeders. Other assumptions are the same as with the previous model. M packers and N feeders are in the market, and the total contracted feeder number remains S. The spot market price is the same as equation (2).

We assume that the contracts are made one period ahead and that contracted feeders will produce the quantity based on the expected spot market price of the delivery period. Thus, the supply equation of the contracted feeder is adjusted as $q^s_{j,t} = Ep_t$. Substitute this contract quantity into packers' total profit function, so $\pi_{i,t} = (R - p_t)(q^d_{i,t} + n_i q^c_t) = (R - p_t)(q^d_{i,t} + n_i Ep_t)$, $i = 1,...,M$. When the market reaches equilibrium, the spot market prices from different time periods will be the same, which means $Ep_t = p_t$. Substitute this condition and equation (2) into the profit function, and take the first order condition with respect to the packers' procurement quantity $q^d_{i,t}$, and the result is the packers' reaction functions:

(7) $$q_{i,t}^{d} = (N-S)R/2 - (N-S+2n_i^c)\sum_{i'\neq i} q_{i',t}^{d} \Big/ [2(N-S+n_i^c)], \text{ for all } i = 1,...,M .$$

Simultaneously solving these reaction functions of M packers for the aggregate demand $Q^d = \sum q_{i,t}^d$ in the spot market and then substituting the result in the market clearing equation (2), we get the spot market clearing price in equilibrium as

(8) $$Ep = R[(N-S)M + S]/[(M+1)(N-S)+2S].$$

From this result, we can see that without captive supplies, which means $S = 0$, the equilibrium price is still the Cournot level. If we restrict the oligopsony model to be a duopsony model by setting the number of packers $M = 2$, this spot market price becomes $Ep = R(2N-S)/(3N-S)$, which is higher than that in the previous model. For example, when $S = N/2$, the spot market price is $3R/5$, which is higher than the monopsony level $R/2$ but lower than the Cournot duopsony level $2R/3$.

From the results above, we can see that with a fixed number of contracts and with supply response, the spot market price level is higher than without supply response. But, captive supplies still reduce market prices.

Flexible Contracts and Flexible Quantity per Contract

Now assume that in the long run, feeders who sign captive supply contracts have a supply response and packers can adjust their captive supply contract numbers and the procurement quantity in the spot market. First, packers choose their number of contracts. The contract ratio x^c is packer's captive supply choice variable:

(9) $$x_{i,t}^c = n_{i,t}^c / N ,$$

where $x_{i,t}^c$ is the contract ratio of packer i, which indicates the percent of feeders out of the total number of feeders with whom packer i contracts in time t. Then feeders decide how many cattle they will produce based on their expectation of the market price. We can reasonably assume that feeders expect the spot market price of the next period will be the same as the current one. Thus, with a linear supply function that has an intercept of zero and a slope of one, feeders will deliver $q_t^c = p_{t-1}$ to their contracted packers. Packers then decide how many cattle to procure in the spot market. Thus, packers' profit function changes to:

(10) $$\pi_{i,t} = (R-p_t)(q_{i,t}^d + n_{i,t}^c q_t^c) = (R-p_t)(q_{i,t}^d + n_{i,t}^c p_{t-1}), \text{ for all } i = 1,...,M .$$

The maximization of the above functions involves variables in multiple time periods and the current period contains two choice variables for each packer. Finding an analytical solution to such a dynamic game would be difficult. We use an agent-based model to simulate this market, but there may be other numerical methods that could also be used. In the following section, we introduce the market design of the agent-based model for an artificial oligopsony market with captive contracts.

Agent Based Artificial Fed Cattle Market with PSO Algorithm

Our main motivation in using the agent-based model is that it allows solving a problem that would otherwise be intractable. But, the relatively simple rules considered in the agent-based model may also be closer to the way actual feeders and packers make decisions than the full rationality assumed in most analytical models. The agents here have either one or two choice variables. The choice variables are how many cattle to purchase in the spot market and how many cattle to purchase via contract. Agents pick the value of their choice variables this time period as a random function of what rules were most profitable last time period. Such agents are boundedly rational (Simon 1957) since they are using heuristic rules rather than an optimization. This "trial and error" method can lead to the market equilibrium and often has the same solutions as analytical models, but is not assured to do so (Young 2009).

The agent-based model contains multiple programmed agents. Here, the programmed intelligent agents act as N feeders and M packers in a simulated fed cattle market. Feeders are price takers, and packers compete for cattle both with captive supply contracts and in the spot market. The transactions between packers and feeders occur in a captive contract market and in a spot market. We set up three simulation procedures: a) fixed number of contracts and fixed quantity per contract; b) fixed number of contracts and flexible quantity per contract, and c) flexible number of contracts and flexible quantity per contract. Figure 1 illustrates how packers and feeders dynamically make their transactions under these market designs.

In the simulation, we assume that packers choose quantities and that market participants discover the interception point of the current aggregate demand and supply curve and use it as the market clearing price (this is imposed by solving for the market clearing price using equation (2)). If no captive supply is present, the simulation results should be exactly what the Cournot theory predicts. Since packers cannot form enforceable agreements with each other, if any market power is exercised which makes the spot market price lower than the Cournot result, it must be done through captive supply.

Figures 1(a) and (b) show the time lines with short run and long run periods. In the short run, we assume that both the captive contract and the quantity per contract are fixed. Under this assumption, we simulate the behavior of packers to show how they adjust their spot market procurement quantity. This process means that during the short run simulation, packers only have one choice variable, the procurement ratio in the spot market. Different from the short run model, figure 1(b) shows that in the long run, packers can select the number of contracts as well as the procurement ratio in the spot market. The process of choosing parameters is called learning. The learning of packers is modeled with a particle swarm optimization algorithm. By playing the game repeatedly, packers can learn from their own experiences and adopt the best strategy for themselves.

Particle Swarm Optimization Algorithm

We use a particle swarm optimization algorithm to model the learning behavior of agents. Past research using agent-based models have used either genetic algorithms (e.g. Vriend 2000) or reinforcement learning (e.g. Waltman and Kayak 2008). Particle swarm optimization more closely matches the way decisions are made in cattle markets and it is potentially quicker at finding equilibrium, but it is expected to reach a similar answer to other learning methods (Zhang and Brorsen 2009). With particle swarm, agents have their own parallel clones and each agent's clones share information only with each other. This kind of marketing strategy can be observed in many real markets. In the fed cattle market, packing firms have multiple packing plants and each plant has their own buyers. Each plant may have different goals about how many cattle it wants to purchase, but each plant will share information within the company at the end of each period and adjust their strategies to increase profit. This sharing of information does not typically occur with genetic algortihms, and this may explain why PSO leads to faster convergence.

Past agent-based models have studied oligopoly rather than oligopsony so new market equilibrium rules are required. Each plant picks the desired quantity slaughtered. Feeders produce a quantity based on last period's price. If feeders produce extra cattle, they can be held over to the next period at no cost[2]. If there are not enough cattle to meet the packer's desired quantity, the available cattle are split between the packers proportional to their desired quantity. The price of feeder cattle is determined as in equation (2) and all packers pay the same price. The downstream demand is assumed perfectly elastic and such that the packer will break even by paying $100 for the cattle. This perfectly elastic downstream demand is necessary so that the packers have no oligopoly power, which is necessary to study oligopsony only and match our theory.

In the markets simulated here, each plant faces a changing economic environment since the plants of the other packers continuously update their strategies. We set up K separate parallel markets, and each packer has a plant in every market. For example, with 20 parallel markets, packers each have 20 plants as the population with which they share information. Although having the same behavioral rules, the K plants of one packer may take a different strategy in each market since the initialized random values are different. In the simulation, plants dynamically change their marketing strategies with the PSO algorithm but feeders are price takers and simply sell their products at the market price.

Suppose the k^{th} plant of packer i chooses $x_{i,k}^{\Gamma}$ as one of its two strategy parameters, $x_{i,k}^{\Gamma} \in [0,1]$, and each strategy parameter is initialized at the beginning of the simulation with a random draw from a uniform distribution, here Γ indicates the strategy variable (quantity purchased in the open market or purchased through captive supplies). Each plant has a velocity, $v_{i,k}^{\Gamma} \in [0,1]$, which determines the change of the strategy value. The changes of choice variables are influenced by the value of the best solutions achieved by

[2] We alternatively ran the model by letting the price adjust and not letting any cattle being held over. The conclusions are not fragile with respect to this change in assumptions.

the k^{th} plant itself, $p_{i,k}^{l,\Gamma} \in [0,1]$, and by the best solution among all of packer *i*'s plants, $p_i^{g,\Gamma} \in U[0,1]$. The superscripts *l* and *g* indicate local and global, the subscripts *k* and *i* indicate k^{th} parallel market and i^{th} packer respectively. Profit function $\pi_k(\mathbf{x}_{i,k})$ is used to evaluate the performance of each decision set $\mathbf{x}_{i,k} = [x_{i,k}^q, x_{i,k}^c]'$.

In every simulation step, each strategy of the k^{th} plant of packer i is selected as

(11) $$x_{i,k,t+1}^{\Gamma} = x_{i,k,t}^{\Gamma} + v_{i,k,t}^{\Gamma} \text{ and}$$

(12) $$v_{i,k,t+1}^{\Gamma} = w \cdot v_{i,k,t}^{\Gamma} + c_1 u_1 (p_{i,k,t}^{\Gamma,l} - x_{i,k,t}^{\Gamma}) + c_2 u_2 (p_{i,k,t}^{\Gamma,g} - x_{i,k,t}^{\Gamma}),$$

where $x_{i,k,t}^{\Gamma}$ indicates the strategy, $v_{i,k,t}^{\Gamma}$ is the velocity vector, $u_\zeta \sim U[0,1]$, $\zeta = 1,2$ are uniformly distributed random numbers, c_1 and c_2 are learning parameters and are called the self confidence factor and the swarm confidence factor, w is an inertia weight factor, $p_{i,k}^{\Gamma,l}$ is the current local best parameter for plant *k* of packer *i*, $p_i^{\Gamma,g}$ is packer *i*'s global best strategy parameter, and the value of Γ is *d* or *c* to indicate strategy parameter x as procurement ratio or contract ratio. The calculated value of $x_{i,k,t+1}^{\Gamma}$ or $v_{i,k,t+1}^{\Gamma}$ is truncated to be one or zero when it overflows the range.

The following equations indicate how to choose $p_{i,k}^{\Gamma,l}$ and $p_i^{\Gamma,g}$ among all parameters of plant i. Under a dynamic environment where plants' best response strategy depends on how others respond, the fitness value of the previous local best may not be the same when it is used in the current economic environment. The best locals of the previous *L* iterations are retested under the current market environment. The current best local is chosen from the past best performance parameters $p_{i,k,t'}^{\Gamma,l}$ and the current strategy:

(13) $$p_{i,k,t}^{\Gamma,l} = \arg\max\left\{\pi_k(\mathbf{p}_{i,k,t-1}^{l}), \ldots, \pi_k(\mathbf{p}_{i,k,t-L}^{l}), \pi_k(\mathbf{x}_{i,k,t}^{\Gamma}) \middle| \mathbf{x}_{i'\neq i,k,t}^{\Gamma}\right\},$$

where $k = 1,2,...,K$ and i' indicates packer i's rivals. The best global parameter is selected from the best local parameters:

(14) $$p_{i,t}^{\Gamma,g} = \arg\max\left\{\pi_1(\mathbf{p}_{i,1,t}^{\Gamma,l}), \ldots, \pi_K(\mathbf{p}_{i,K,t}^{\Gamma,l})\right\},$$

where K is the total number of parallel markets.

Equilibrium Criterion

The parameters used in the three scenarios are shown in table 1. The market parameters and PSO parameters are the same for all scenarios and the packer number *M* is 2 in the duopsony market and 4 in the oligopsony market. There are 400 feeders in each market. A simulation run contains multiple iterations so that agents repeatedly play the game until the market reaches equilibrium. We use 100 runs for each of the 12 experimental settings with different random starting values and report the average equilibrium of the 100 runs. This approach is similar to the method of random restarts that is commonly used with stochastic global optimization methods (Hamm, Brorsen, and Hagan 2007). Within each simulation run, we let agents trade until equilibrium is reached as determined by the convergence criterion or a maximum of 500 iterations is reached. The limit of 500 iterations was sometimes reached in the four-packer case and these observations are included in the averages that we compute.

Typically, zero diversity in the population's strategies among all markets signals the stopping point for a PSO. Zero diversity means that no packer has an incentive to change strategies given the strategies of other packers. As the population evolves, diversity diminishes and each agent uses the same strategy in each parallel market. Our convergence criteria is that the variance of each agent’s strategies in the population must be less than 0.01% and the variance of the mean value of the strategies for 10 generations must be less than 0.01%.

The inertia weight *w* in (12) is critical in affecting the speed of convergence (Chatterjee and Siarry 2006). A large inertia weight provides a larger exploration but slow convergence, while a smaller inertia weight is needed to fine-tune the current search area. It is worth making a compromise, such as starting with a higher value at the beginning and then decreasing *w* with iterations:

(15) $$w_t = \beta_0^w + \beta_1^w (t_{\max} - t)/t_{\max} ,$$

where $t_{\max}$ is the maximum number of iterations and *t* is the current iteration. Self confidence and global confidence factors c_1 and c_2 in equation (12) can be set as constant and are usually between 0.5 and 2.5. Here we choose 1 for both of them.

Summary of Simulation Procedure with PSO

There are *M* packers and *N* feeders. Each packer and feeder has one packing plant in each of the *K* parallel markets. Each plant of a packer may have a different trading strategy in each parallel market. The steps in the simulation are:

(i) In each market, randomly initialize $x_{i,k,t}^{\Gamma}$ and $v_{i,k,t}^{\Gamma}$ for all i. We choose the quantity ratio $x_{i,k,t}^{\Gamma} \sim U[0,1]$ and $v_{i,k,t}^{\Gamma} = 0$ for all $i = 1,..., M$, $k = 1,..., K$, and $t = 1,..., L$.

(ii) Select the best locals for each plant with equation (13).

(iii) Select best global for each packer with equation (14).

(iv) While the market is not converged, each packer continuously uses functions (11) and (12) to select new strategies.

Pseudocode describing the agent-based model is available in a supplementary appendix online and the executablel Java code is available at http://www.openabm.org under the title Particle Swarm Optimization Algorithm [pso_captivesupplyeffect].

In each of the three scenarios, we determine the market equilibrium of a duopsony market and an oligopsony market containing 4 packers. Thus, we have 6 simulation settings.

In the short run simulation, the captive contracts are fixed, and packers interact in the market to find the optimal procurement strategies. We simulate the market by letting packers contract with 50% of feeders in the duopsony market and 75% of feeders in the four-packer market. Since packers are homogeneous, we can reasonably assume that packers will split the contracts equally, and each of them will contract with 25% of the total feeders in the duopsony market and 18.75% in the four-packer market.

With the number of contracts fixed and with contract supply response, we set the quantity per contract as 50. According to our theoretical derivation, if packers contract with $(M\text{-}1)N/M$ feeders and the contract quantities are fixed at the monopsony level $R/2$, packers can depress the spot market price to the monopsony level. So we use this setting to test if packers in the artificial market can learn to find the optimal procurement strategies to benefit from the monopsony price in the spot market. Thus, for the first two scenarios, packers have one choice variable - the procurement ratio; but in the long run, they have two choice variables - the contract ratio and the procurement ratio.

Simulation Results

The mean and standard deviation of the market price and packers' strategies at equilibrium from 100 runs are in table 2. The standard deviations in table 2 are small, which shows that local optimums are not a problem since solutions are close to the same regardless of the random starting values selected. The simulation results in table 2 closely match the predictions of the theoretical models. In the short run with no supply response, packers can depress the spot market price to the monopsony level of $50 for both the duopsony market and the oligopsony market, which matches Xia and Sexton (2004). When a supply response is added, the expected solution from equation (8) is $60 for duopsony and $63.6 for the four-firm case. The agent-based model results match closely for the duopsony case, but with the four-firm case, the computerized packers miss a little of the potential market power from captive supplies and end up with prices slightly above the theoretical prediction (this could mean that the agent-based model is not always completely converged in the four-firm case).

In the long run when packers choose both spot market and contract quantity, packers compete to obtain the Cournot results, and the spot market price is $66.7 in the duopsony market and around $80 in the four-packer market. In addition, when packers choose both the number of captive supply contracts and the procurement quantity in the spot market, packers mostly use the spot market to purchase cattle. This result means that in the long run, packers cannot use captive contracts to depress the spot market price, and packers behave like they do not need captive supplies as an alternative procurement method. Intuitively, it should not be a surprise that the captive supplies do not provide long-run market power and that the long-run solution is the Cournot solution. The market equilibrium condition in equation (2) causes the level of captive supplies to eventually be driven to zero so that the Cournot solution can be reached.

Besides the statistical analysis of the market equilibrium, figures 2 and 3 show the dynamics of the spot market price and the packers' strategies in an individual run under example experimental settings. These figures illustrate how the particle swarm algorithm proceeds toward equilibrium. Note that each figure represents a single set of initial starting values while the means in table 2 are averages over 100 runs. Figure 2 shows the market prices for the duopsony and 4-packer models under the long run assumption and the short-run assumption with a fixed contract without contract supply response. From figure 2, we can see that if packers make long term contracts with feeders and the quantity of contracts are fixed to a carefully chosen value, they can depress the spot market price to the monopsony level of $50 even without collusion. However, without long term contracts where packers adjust strategies on both captive supply and spot market procurement, the spot market price goes to the Cournot solution.

Figure 3(a) shows the simulation results of the duopsony market under fixed contracts without contract supply response. The figure shows that at equilibrium, each packer uses a procurement ratio of 12.5% as its optimal strategy, which yields a spot market procurement quantity of 5,000 according to equation (1) since *R* and *N* equal $100 and 400. Thus, the total demand in the spot market is 10,000. Substituting this quantity and the number of uncontracted feeders of 200 into equation (2), we see that the market price is $50. This result is consistent with our simulation results in figure 2 and the theoretical results in equation (5') of Xia and Sexton (2004).

Following the method above, we simulate the four-packer market by letting packers contract with 75% of the total feeders. The contract quantity is also fixed at 50. The simulation results in Figure 3(b) show that the market reaches equilibrium when each packer uses a spot procurement ratio around 3.125% as its strategy. Substitute these values into equation (5), and we get a market price of $50. These results are consistent with our simulated results in figure 2. The results confirm that when the market contains more packers, the packers need to contract with more feeders than the duopsony market to depress the spot price to the monopsony price level.

The results leave open the question of what changes in assumptions would lead to results that match empirical observations about cattle markets. The agent-based model was designed more to match the theory than to match actual cattle markets. Note that the simulation with human subjects by Ward et al. (1999) more closely matched both the process of actual cattle markets and the empirical findings that the market power created by captive supplies is small. The Cournot assumption of packers choosing quantity still leads to market power that is considerably greater than most empirical estimates of market power. In addition, since packers use captive supplies, the model still shows that the use of captive supplies would lead to market power. Further, the model leaves open the question of why packers use captive supplies. A theoretical model that matched empirical observations about the cattle market may need to be very different and would likely need to drop the Cournot assumption and provide an alternative motivation for packer use of captive supplies. For example, packers may use captive supplies to assure a supply of cattle of a desired quality or they may use them to reduce the risk of having less than their desired quantity.

Conclusions

An agent-based model is used to study the impact of captive supplies under fixed or flexible contracts. With a fixed number of contracts with or without supply response, analytical solutions are available. For the long-run scenario with flexible contracts and flexible quantity per contract, the solution could not be found with mathematical analysis and an agent-based simulation method is used. The agent-based model has been used in economics but is relatively new to agricultural economics other than in land-use modeling. The agent-based model provides a way to study complex problems that are difficult to solve with mathematical analysis and is less costly than experiments with human subjects.

We first generalize the Xia and Sexton (2004) model to the oligopoly case. As the number of packers increase, more of the available supplies must be contracted in order to get the same price depressing effect. When the Xia and Sexton (2004) model is extended to the long-run case where supply from contract feeders is no longer perfectly inelastic, the price depressing effect of captive supplies is further reduced. The agent-based model gives nearly the same results as the analytical models. The one exception is that the four-packer case with supply response shows slightly less price depressing effect than predicted by the analytical model. When the packers can adjust the number of contracts and feeders have a supply response for contract quantity, the price depression phenomena of captive supplies disappears since packers do not contract any cattle. This result leaves open the question of why packers use captive supplies, but it suggests that it is for reasons other than increasing market power. The results also predict more market power than is estimated empirically. While the research has reduced the gap between theoretical and empirical research there is still a remaining gap that future research may want to address.

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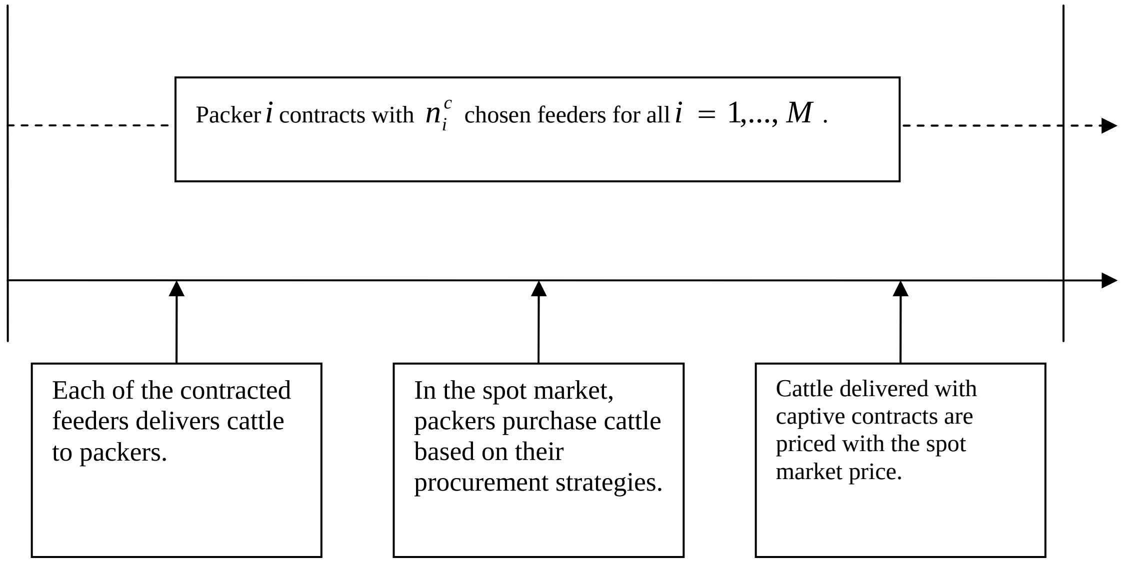
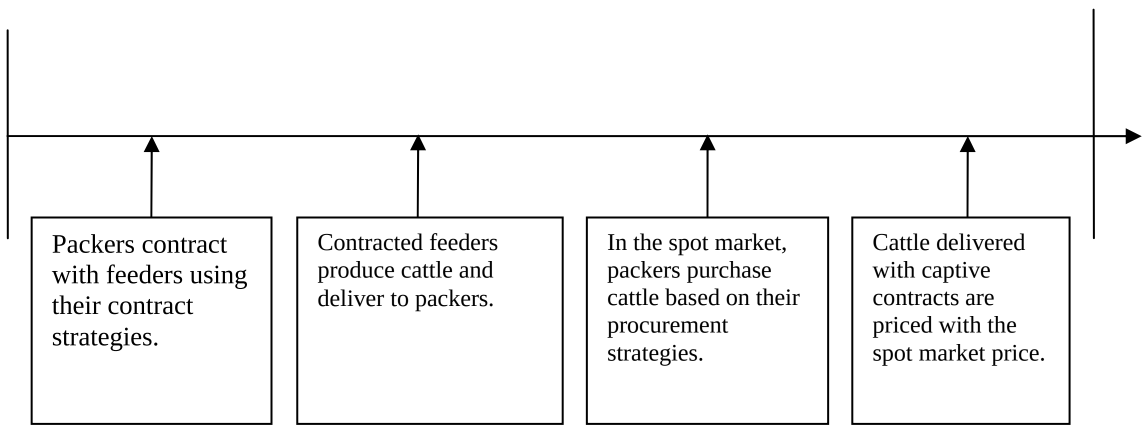


(a). Fixed number of contracts and with or without captive supply response



(b). Long run model with flexible number of contracts and captive supply response

Figure 1. The timeline of the model

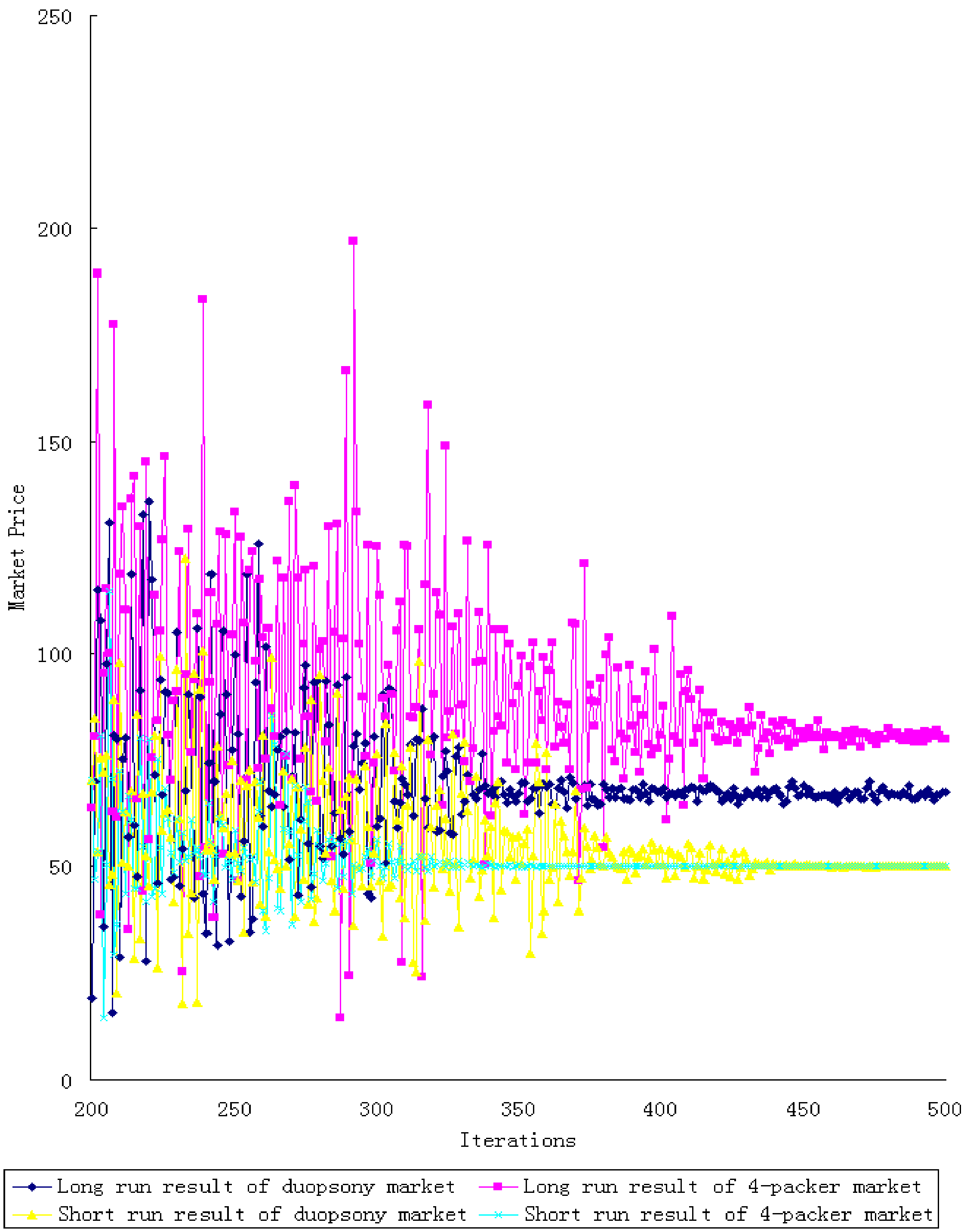
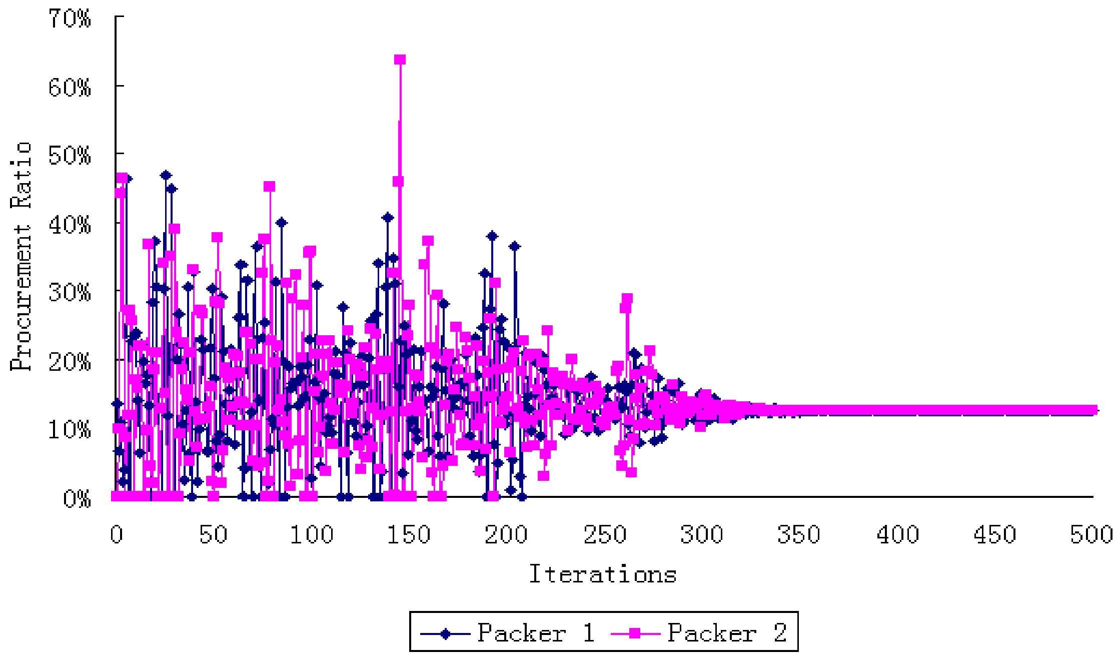
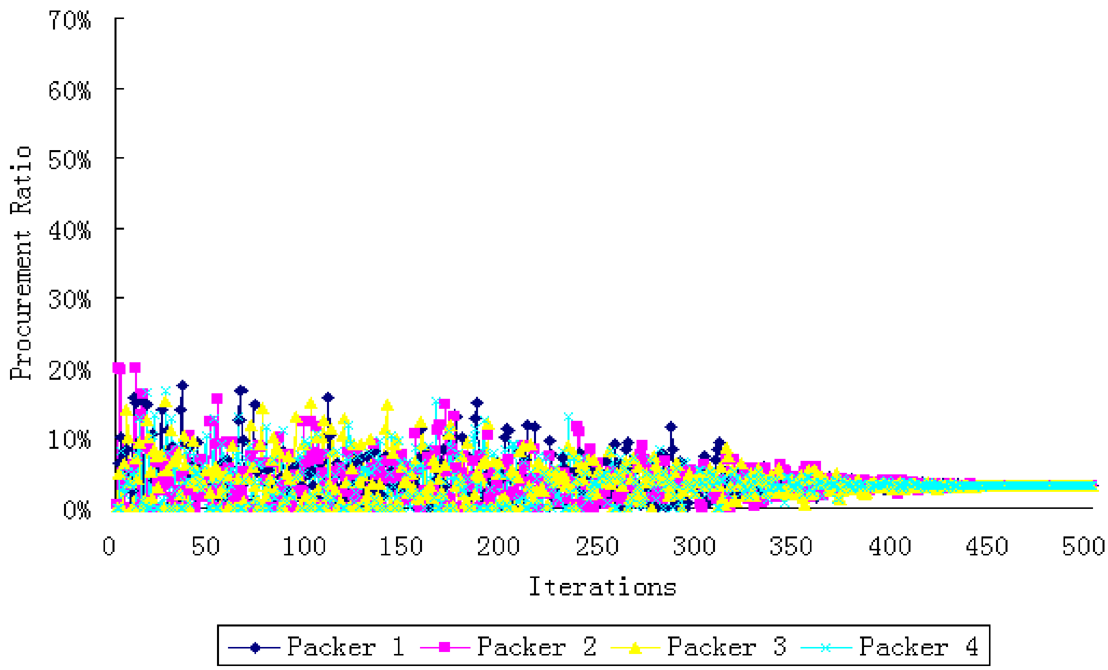


Figure 2. Spot prices of duopsony and four-packer markets

Note: For the two short run settings, both the number of contracts and quantity per contract are fixed.



(a). Duopsony Market



(b). Four-Packer Market

Figure 3. Packers' short run procurement ratio in the spot market without contract supply response

Table 1. Parameter Setting in Artificial Market Simulation Design

Parameter	Symbol	Value
Market Parameters		
Number of Packers	M	2 for duopsony market; 4 for four-packer market
Number of Feeders	N	400
Cattle Value Before Processing	R	$100
Particle Swarm Optimization (PSO) Algorithm Parameters		
Intercept of inertia weight in equation (15)	β_0^w	1.5
Slope of inertia weight in equation (15)	β_1^w	0.5
Self and global confidence factors of PSO	$c_1 = c_2$	1
Number of parallel markets	K	20
Maximum iteration of one simulation run	$t_{\max}$	500
Parameters for Model with Fixed Contracts		
Number of contracted feeders for each packer	n^c	N/4 for duopsony market; 3N/16 for four-packer market
Quantity per captive supply contract	q^c	50

Table 2. Short Run and Long Run Simulation Results of Market Prices and Packers' Strategies under Duospsony Market and Four-Packer Oligopsony Market Settings

Market Structure	Packer	Statistic	Short Run						Long Run			
			Without Contract Supply Response			With Contract Supply Response						
			Market Price	Procurement Ratio	Profit	Market Price	Procurement Ratio	Profit	Market Price	Contract Ratio	Procurement Ratio	Profit
Duopsony		Mean	50.00			60.00			66.76			
		SD	0.00			0.00			0.54			
	Packer 1	Mean		12.50%	500,000		15.00%	480,000		1.55%	32.45%	444,000
		SD		0.00%	0		0.00%	0		1.52%	0.90%	7,539
	Packer 2	Mean		12.50%	500,000		15.00%	480,000		1.89%	32.14%	443,000
		SD		0.00%	0		0.00%	0		1.15%	0.76%	4,702
Four-Packer		Mean	50.00			66.41			80.20			
		SD	0.01			1.20			0.41			
	Packer 1	Mean		3.13%	250,000		4.12%	218,000		0.83%	19.48%	159,500
		SD		0.00%	0		0.34%	9,515		0.79%	0.42%	2,236
	Packer 2	Mean		3.13%	250,000		4.15%	219,000		1.22%	19.07%	158,500
		SD		0.00%	0		0.36%	7,182		0.93%	0.83%	4,894
	Packer 3	Mean		3.13%	250,000		4.20%	220,500		1.16%	19.32%	160,000
		SD		0.00%	0		0.25%	8,256		0.97%	0.58%	3,244
	Packer 4	Mean		3.13%	250,000		4.14%	219,500		1.16%	19.16%	159,000
		SD		0.00%	0		0.25%	8,870		1.05%	0.99%	3,078

Note:

1. In the short run duopsony market, each packer uses a fixed captive contract ratio of 25% , which means it contracts with 100 feeders in every iteration period;
2. In the short run four-packer market, each packer uses a fixed captive contract ratio of 18.75% , which means it contracts with 75 feeders in every iteration period;
3. Contract quantities are fixed at 50 for short run markets without contract supply response.