Concentration and Resiliency in the U.S. Meat Supply Chains

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Meilin Ma
Department of Agricultural Economics
Purdue University

Jayson L. Lusk
Department of Agricultural Economics
Purdue University

Supply chains for many agricultural products have an hour-glass shape; in between a sizable number of farmers and consumers is a smaller number of processors. The concentrated nature of the meat processing sectors in the United States implies that disruption of the processing capacity of any one plant, from accident, weather, or as recently witnessed – worker illnesses from a pandemic – has the potential to lead to system-wide disruptions. We explore the extent to which a less concentrated meat processing sector would be less vulnerable to the risks of temporary plant shutdowns. We calibrate an economic model to match the actual horizontal structure of the U.S. beef packing sector and conduct counter-factual simulations. With Cournot competition among heterogeneous packing plants, the model determines how industry output and producer and consumer welfare vary with the odds of exogenous plant shutdowns under different horizontal structures. We find that increasing odds of shutdown results in a widening of the farm-to-retail price spread even as packer profits fall, regardless of the structure. Results indicate that the extent to which a more diffuse packing sector performs better in ensuring a given level of output, and thus food security, depends on the exogenous risk of shutdown and the level of output desired; no horizontal structure dominates. These results illustrate the consequences of policies and industry efforts aimed at increasing the resilience of the food supply chain and highlight that there are no easy solutions to improving the short-run resilience by changing the horizontal concentration of meat packing.

Keywords: market concentration, risks, supply chain resiliency, U.S. beef market

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1. Introduction

Concentration in the U.S. meat packing sector has increased markedly from the 1960s to the 1990s (MacDonald et al., 1999). In 2019, the 22 largest beef packing plants, representing just 3.3% of all plants, were responsible for 71.7% of federal inspected cattle processing in the United States (National Agricultural Statistics Service or NASS, 2020). Pork packing is similarly concentrated with the largest 15 plants, representing only 2.5% of all plants, responsible for 61.9% of all federally inspected hogs slaughtered (see appendix 1). The high level of horizontal concentration can be explained, at least in part, by the economies of scale in meat packing (Koontz and Lawrence, 2010; MacDonald, 2003; MacDonald and Ollinger, 2005; Morrison Paul, 2001), implying that, in normal times, large and cost-efficient packing plants result in more affordable meat for consumers and higher livestock demand than would be the case with a more diffuse and higher-cost packing system.

However, times are not always normal, and unexpected events can lead to plant shutdowns. For example, in August 2019, a fire at a beef packing plant in Kansas, responsible for about 5% of the total U.S. processing capacity, caused a spike in the farm-to-retail price spread and led to lawsuits and a federal investigation (USDA, 2020). Then, in April and May 2020, worker illnesses from COVID-19 led to the shutdown of a number of large beef and pork packing plants, as roughly 40% of processing capacity was brought offline, leading to an unprecedented increase in the farm-to-wholesale price spread and serious concerns over food security and meat supply (Lusk, Tonsor, and Schulz, 2021). These recent events have raised questions about the resilience of the beef and pork supply chains, and policy makers have sought ways to encourage the entry of more small and medium-sized processors, hoping to enhance the resilience (Bustillo, 2020; Nickelsburg, 2020; Pitt, 2021). Despite these efforts, at present, it remains unclear whether and to what extent a less concentrated meat packing sector would have performed better during the pandemic, a knowledge gap this paper aims to rectify.

Resilience is a widely discussed topic across disciplines, like ecology, sociology, and management, and the definition of resilience is disciplinary specific (Bhamra et al., 2011). Regarding the resilience of the supply chain, researchers mainly study the short-run as well as long-run adaptive capability of a supply chain to respond to disruptions and maintain operations at the desired level (Ponomarov and Holcomb, 2009). In our context, we evaluate resilience of the U.S. meat supply chain based on *the short-run performance of different horizontal structures in achieving target output and producer/consumer welfare, in response to an exogenous chance of shutdown faced by packing plants*.

Our model of the U.S. meat supply chain captures key features of the meat packing sector, including its concentrated nature and economies of scale. The concentrated nature of meat packing has been the subject of much attention, and numerous studies have attempted to estimate and determine the presence or extent of imperfect competition in the sector, finding mixed evidence (e.g., see Wohlgenant, 2013 for one review). Our model allows heterogeneous packers to exercise market power under Cournot competition, though packers may not exercise much seller or buyer power under a particular horizontal structure.

Legal complaints and livestock producer concerns have focused on the farm-to-wholesale or farm-to-retail price spreads as evidence of market power, and concerns about widening price spreads have been reignited by price dynamics following recent plant shutdowns. Our model and findings re-enforce Brester, Marsh, and Atwood's (2009) results that price spreads, in isolation, are uninformative as it relates to market power and packer profits. A few recent papers have explored the market impacts that occur, when a firm decides to close down one of its packing plants (e.g., McKendree, Saitone, and Schaefer, 2021; Raper, Cheney, and Punjabi, 2006). Our paper goes beyond this prior work by introducing a broader framework that allows us to explore outcomes resulting from differing horizontal structures, and when plants in the industry face an exogenous risk of shutdown rather than the endogenous choice to reduce capacity.

This paper is organized as follows. In section 2, we set up a three-stage theoretical model to characterize the interactions among livestock farmers, meat packing plants, and retailers. Because entering the meat packing sector requires considerable fixed investment in constructing the plant (i.e., sunk costs), the processing capacity of each plant is assumed to be fixed in our short-run context. We allow the plants to Cournot-compete by choosing the optimal production scale in the scenario with no exogenous risk of shutdown, given size-specific heterogeneous processing cost functions. Under Cournot competition, the degree of seller and buyer power exercised by a packing plant is determined by its volume share in the sector.

To calibrate the model, we impose linear functions to beef demand and cattle supply to obtain analytical solutions for equilibrium prices, quantities, and welfare measurements in section 3. The demand elasticity, supply elasticity, and marginal costs of retailing are collected from recent empirical studies and government statistics. Given these parameters, marginal costs of processing are specified to ensure that the equilibrium size distribution of plants in the risk-free scenario matches the actual horizontal structure of U.S. beef packing in 2019.

In section 4, we conduct simulations to study counter-factual equilibria in the beef industry under various risk levels and different horizontal structures. For each simulation, a particular level of risk is randomly imposed on all packing plants, causing some plants to shut down. In addition to the actual structure of the beef-packing sector, we consider two alternative structures: a market with small-sized plants only (i.e., the diffuse structure) and a market with large-sized plants only (i.e., the concentrated structure). The actual structure lies in between the two extreme structures.

Simulation outcomes reveal the complexity in the relative resilience across horizontal structures of meat packing. When each plant in the industry faces chance of shutdown equal to 10-30%, for example, simulation results show that a more concentrated packing sector performs better in ensuring a relatively high level of output (e.g., less than 20% output reductions), and thus food security, than a diffuse packing sector, while the reverse is true if the goal is to ensure that output does not fall below a minimal threshold (e.g., more than 40% output reductions). On average, though, differences across horizontal structures are typically not of large economic magnitudes. What distinguishes the three structures is the variation in the prices and quantities across simulations. A more diffuse packing sector has lower variability in output and consumer and producer welfare for any given shutdown risk than a more concentrated packing sector. While lower variability might be interpreted as a benefit of a diffuse packing sector, it need not be the case as it might imply certainty of a poor outcome. Sensitivity analysis suggests that these patterns are robust to alternative values of key parameters, including supply elasticity, and alternative structures and assumptions on the plant-level output. Similar conclusions apply to the pork supply chain which has similar structural features as the beef supply chain.

As discussed in section 5, these results help illustrate the consequences of policies and industry efforts aimed at increasing the resilience of the food supply chain. Policy proposals, academic writings, and popular discussions, have tended to focus on lessening the degree of concentration as key to improving resilience (e.g., Hendrickson, 2015; Pitt, 2021; Rotz and Fraser, 2015). Using the beef supply chain as an example, our research shows that the relationship between concentration and resilience is complex. Odds of output, or producer or consumer surplus, falling below a given level is sometimes lower and sometimes higher when the packing sector is less concentrated; however, it is generally the case that a more diffuse packing sector has slightly lower odds of witnessing the worst possible outcomes. However, total expected welfare is typically lower under a more diffuse packing sector because of the lost economies of scale, a result related to findings such as that by Azaam and Schroeter (1995) who show welfare losses from market power are more than offset by improved cost efficiencies. However, if the social planner is risk averse, especially loss averse, a more diffuse structure may be preferred (see section 4.3).

Despite the sizable literature on concentration and market power in meat packing, our study is among the first to relate these issues to the short-run resilience to exogenous (or “disaster”) shutdown risks on packing plants. Given the severe adverse impacts of COVID-19 on livestock and meatpacking sectors, and impending policy changes and legal challenges to the present system, it is of high importance to understand how short-run resilience may be impacted by degree of concentration.

2. Conceptual Model

Given heterogeneity in size of processors in the U.S. meat-packing industry, we employ a Cournot competition model to characterize plant interactions. The Cournot model offers an appropriate framework for our context because a meat processor is committed to producing at a particular scale upon building its plant.[1] Once the plant is built, the processor tries to, and often does, produce near full capacity where costs are minimized (Koontz and Lawrence, 2010; Bina et al., 2021). It is hence reasonable to model plants competing in quantity, which implies rising marginal costs of

[1] This model does not account for spatial factors related to plant location. In reality, all the largest beef packing plants are located in a tight geographic region around the Texas panhandle, Western Kanas, and Nebraska, suggesting that distance is unlikely to be a predominant factor affecting competition.

processing at the full capacity or increasing shadow value of relaxing the capacity constraint of a given plant. The model also allows for imperfect competition in the cattle as well as beef retail markets, and can consider various counter-factual structures of the meat-packing sector.

Let there be *n* processing plants of different sizes. The plants are denoted by $i \in \{1,2,3 \dots n\}$. Relatively large processors enjoy economies of scale and have relatively low marginal costs of processing than smaller processors (Koontz and Lawrence, 2010; MacDonald, 2003; MacDonald and Ollinger, 2005). Under Cournot competition, a processor with lower marginal costs always produces at a larger scale in equilibrium.

Prior studies find that meat processors exercise buyer power against livestock producers and may also exercise seller power against retailers (Wohlgenant, 2013). We hence specify an upward sloping supply function and a downward sloping inverse demand function faced by the processors. The inverse demand function that processors face is derived from the inverse demand function for beef less a constant retailing marginal cost (c^r):

(1a) $P^r = D(Q^r|X)$,

(1b) $P^w = P^r - c^r = D(Q^r|X) - c^r$,

where P^r is the retail price, P^w the wholesale price, and X demand shifters. The inverse farm supply of cattle is expressed as:

(1c) $P^f = S(Q^f|Y)$,

where P^f is the farm-gate price and Y supply shifters.

Assume for convenience that the processing technology satisfies quasi-fixed proportions, so that no substitution is permitted between cattle and other processing inputs like labor and energy in producing beef products. Without loss of generality, we can hence measure total quantities at farm, processor, and retail stages in the supply chain as $Q^r = Q^w = Q^f = Q = \sum_n q_i$ where q_i denotes the output of a packing plant.

Assuming a constant marginal cost of processing for each packing plant, we express the total cost of plant i as:

(2) $$C_i^w = c_i^w q_i + P^f(Q) q_i,$$

where c_i^w is a constant marginal cost of processing and decreases in the size of the plant. We then write a profit-maximizing processor's objective function as:

(3) $$\pi_i^w = (D(Q|X) - c^r) q_i - \left(c_i^w + P^f(Q|Y)\right) q_i.$$

Taking the derivative with respect to q_i gives the first order condition:

(4) $$P^r\left(1 - \frac{\xi_i^w}{\eta^w}\right) - c^r = P^f\left(1 + \frac{\theta_i^f}{\epsilon^f}\right) + c_i^w,$$

where $\xi_i^w = \frac{\partial Q}{\partial q_i}\frac{q_i}{Q} \in [0,1]$ is the market power parameter of a particular processor against retailers and indicates processor's seller power (Perloff, Karp, and Golan, 2007), η^w is the absolute value of demand elasticity for the meat, θ_i^f is the market power parameter of a particular processor against farmers and measures processor's buyer power, and ϵ^f is the elasticity of farm supply. When the market power parameter equals zero, there is perfect competition in the corresponding market. The closer the market power parameter is to one, the more market power exercised by the processing plant.

Under Cournot competition, $\xi_i^w = \frac{\partial Q}{\partial q_i}\frac{q_i}{Q} = \frac{\partial Q/Q}{\partial q_i/Q_i} = s_i = \theta_i^f$, meaning that the market power parameter of a processor equals its output share in the market.[2] As illustrated in section 3,

[2] One might be concerned about the common ownership across packing plants in the meat industry. For instance, the largest four meat packing companies own most of the large-sized plants. Our model is readily able to incorporate common ownership by letting $\frac{\partial Q}{\partial q_i}$ be larger than 1. That is, when a plant changes its output levels, other plants

we calibrate output shares of plants based on the actual distribution of plant sizes. Taking the actual horizontal structure of beef packing in 2019 as an example, the market shares of largest plants are merely 3-5%, implying limited exercise of market power in the processing sector.

3. Parameterization

To apply this framework to the U.S. livestock industry, we need to obtain analytical solutions from the general model by assigning functional forms, choosing plant sizes to be considered, and obtaining values of parameters. Referring to NASS (2020), we take the most recent, pre-COVID size distribution of beef packers in the United States as the benchmark to characterize the risk-free horizontal structure. The pork packing sector has a similar structure.

As detailed in appendix 1, the nine size groups reported by NASS are consolidated into three groups. Plants with yearly output of 1-49,999 head account for 91.8% of all plants, but contribute only 3.1% of the industry output. Their average annual output is 1.7 thousand head per plant. Plants with yearly output of 50,000-499,999 head account for 4.9% of all plants and contribute 25.2% of the total output. On average, their annual output is 252.3 thousand head per plant. Finally, 3.3% of the plants slaughter over half million head per year and contribute 71.7% of industry output. Their average annual output per plant is as large as 1.1 million head. Throughout the rest of this article, we rely on the three output groups referred to as the small-sized, medium-sized, and large-sized beef packers, respectively.

3.1 Analytical Solutions

We utilize linear inverse demand and supply functions faced by meat packers, respectively:

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belonging to the same company would do the same. Doing so results in a smaller Q^* and gives large-sized plants more market power, but would not change our central insights in the distribution of simulated outcomes across structures. Moreover, our main focus is on risks of shutdown, which occur at the plant, not ownership level.

(5a) $P^r = a - \alpha Q,$

(5b) $P^f = b + \beta Q.$

Assume that perfect competition is achieved with a large number of small-sized processors in the industry. Normalizing the equilibrium retail price and quantity under perfect competition to 1, we are able to express the competitive wholesale price as $1 - c^r$ and the competitive farm price as $f = 1 - c^r - c_S^w$, where the S subscript indicates small-sized plants. It follows that $\alpha = \frac{1}{\eta^r}$, $\beta = \frac{f}{\epsilon^f}$, $a = 1 + \frac{1}{\eta^r}$, and $b = f - \beta$.

Rewriting the first order condition of a processing plant i as:

(6) $P^r - c^r - P^f - c_i^w = -q_i\left(\frac{\partial P^r}{\partial q_i} - \frac{\partial P^f}{\partial q_i}\right),$

we obtain:

(7a) $(a - \alpha Q) - (\, b + \beta Q) - c^r - c_i^w = (\alpha + \beta) Q \frac{\partial Q}{\partial q_i} \frac{q_i}{Q}.$

Because $\frac{\partial Q}{\partial q_i} \frac{q_i}{Q}$ equals the production share of plant i, adding up over the n plants yields:

(7b) $n(a - b) - n(\,\alpha + \beta) Q - nc^r - \sum_i^n c_i^w = (\alpha + \beta) Q.$

Equation (7b) implies the equilibrium industry output is:

(8a) $Q^* = \frac{n}{n+1} \frac{(a-b) - c^r - \overline{c^w}}{\alpha + \beta},$

where $\overline{c^w} = \frac{\sum_i^n c_i^w}{n}$ is the industry-level average processing marginal cost.

With Q^*, it is easy to compute the equilibrium prices P^{r*} and P^{f*}. Because we assume linear functional forms for demand and supply, we compute consumer surplus (CS), producer surplus (PS), and processor profits (Π) as:

(8b) $CS = \frac{(a - P^{r*}) Q^*}{2},$

(8c) $PS = \frac{(P^{f*}-b)Q^*}{2}$, and

(8d) $\Pi = (P^{r*} - c^r - P^{f*})Q^* - \sum_i^n c_i^w q_i^*$.

The equilibrium production of plant i is solved by plugging Q^* into equation (7a). Re-arranging the equation, we see that plant i's output is given by:

(8e) $q_i^* = \frac{(a-b)-c^r-c_i^w}{\alpha+\beta} - Q^*$.

Given a shutdown shock imposed on each plant, some plants stop operation, leaving $n' < n$ active plants in the sector. In the short-run, we do not allow the remaining n' plants to Cournot-compete and achieve new equilibrium production scales, because building new production capacity takes considerable time and is unlikely due to temporary shutdowns of competitors. Thus, the new total quantity processed is:

(9a) $Q' = \sum_{n'} q_i^*$.

Correspondingly, the new market equilibrium retail price and farm price can be found based on the demand and supply functions that are unchanged under the shock on processing plants. In the new equilibrium, c_i^w rises to ensure that the initial output levels are equilibrium values in a new equilibrium with n' active plants. The implied processing marginal costs are higher than the initial values and equal:

(9b) $c_i^{w\prime} = (a-b) - c^r - (\alpha+\beta)(q_i^* + Q')$.

In sensitivity analysis, we relax the assumption of fixed q_i^* and show that main conclusions remain unchanged.

3.2 Parameter Values

The key parameters in our simulation model are the own-price demand elasticity for beef (η^r), the short-run supply elasticity of cattle (ϵ^f), the retail marginal costs (c^r), marginal costs of processing for different sizes of slaughter plants (c_i^w), and the competitive farm share of retail beef value (f). We survey the literature and public statistics to assign appropriate values to the parameters in our baseline simulation model.

To find the plausible value for η^r, we surveyed recent U.S. focused empirical studies on beef demand. These studies use a variety of data sources at different frequencies ranging from individual-consumer survey data, to weekly retail scanner data, to quarterly or annual, aggregate nationwide data. We summarize seven recent studies providing 31 point estimates of demand elasticity in appendix table A2. The estimates range widely and roughly fall in two domains: a low domain from -0.5 to -1, suggesting inelastic demand, and a high domain from -1.7 to -2.3, implying elastic demand. The relatively elastic magnitudes are generally from studies using high frequency data. We take the mean value of the high domain as the baseline value of η^r because our study focuses on short-run changes in the market equilibrium.

Estimating supply responses for products with biological cycles has long been a challenge (Aadland and Bailey, 2001). There are relatively few recent studies providing estimates of cattle supply elasticities in the United States (see appendix table A3 for a few estimated values). The values are quite consistent, suggesting inelastic cattle supply in the short-run, with ϵ^f equal to about 0.2. With respect to our simulation model, however, letting ϵ^f be smaller than one might lead to cases where the equilibrium farm price is negative. Such cases happen when a sufficiently large number of plants shut down, and imply that farmers need to pay plants to get their animals slaughtered to make room for new feeder animals. While these outcomes would be highly unusual, the market might approximate the outcome, as in the case of COVID-19, when hog producers resorted to euthanizing hogs (e.g., Dipietre and Mulberry, 2021). For the purpose of simulations, we restrict P^f to be non-negative by setting the supply elasticity to one, assuming that farmers may enjoy some flexibility in holding the stock for a few days to a couple of weeks if the farm price falls too low. Less elastic supply is considered in section 4.2 where we conduct sensitivity analysis.

The retail marginal cost parameter is approximated by price spreads reported by USDA, Economic Research Service (2021). We assume that a common c^r applies to all sizes of slaughter plants and c^r is independent from shutdown risks. USDA monthly beef price spread data are measured in retail-weight equivalent units based on fixed conversion rates from cattle to processed beef and from processed beef to retail beef (Hahn, 2004). The average monthly wholesale-to-retail price spread margin in 2019 accounts for 41-43% of the retail beef value. In the base simulation, we hence set c^r at the mean value or 0.42 given the competitive retail price is normalized to 1.

To replicate the actual distribution of plant sizes grouped into three levels, we set processing marginal costs for the three sizes of plants such that their risk-free, relative output sizes under Cournot competition match with the actual statistics reported by USDA (see appendix table A1). Normalizing the risk-free output of small-sized plants to 1, the scale of medium-sized plants is 154, and the scale of large-sized plants is 660. Once the marginal costs of processing for the small-sized plants are determined, the farm share under perfect competition is found by $f = 1 - c^r - c_S^w$. The value of f also matches with the farmer share of beef reported by USDA (2021). Baseline parameter values are summarized in table 1.

Table 1. Parameter Values in the Base Simulation

Parameter	Definition	Value
η^r	Magnitude of demand elasticity for beef	1.94
ϵ^f	Supply elasticity of cattle	1.00
c^r	Retail marginal costs	0.42
f	Farm share of the retail value under no risk	0.43
c_S^w	Processing marginal costs, small-sized under no risk	0.16
c_M^w	Processing marginal costs, medium-sized under no risk	0.15
c_L^w	Processing marginal costs, large-sized under no risk	0.12

4. Simulation Results

The calibrated model is flexible in considering various horizontal structures of the U.S. beef packing sector. We consider various risk levels and present baseline simulation outcomes for three horizontal structures of interest. Sensitivity analysis suggests that the baseline outcomes are robust to alternative parameter values and assumptions.

4.1 Baseline Outcomes

In addition to the actual structure, we are interested in two counter-factual horizontal structures of the beef packing sector: small-sized-only and large-sized-only. In the rest of this article, we refer to the actual structure as the "current scenario" where the size distribution of packing plants matches exactly the actual distribution in 2019, when collapsed to three size groups. The small-sized-only is referred to as the "all-small scenario" and characterizes a diffuse structure which is completely occupied by small-sized plants. The third structure is called the "all-large scenario" and characterizes an oligopoly-oligopsony market which is occupied by a few large-scale plants.

For easier comparison across different horizontal structures, we let all the scenarios reach the same equilibrium industry output under no risk.[3] The number of different sized plants are adjusted accordingly. The distribution of plant sizes in each scenario is displayed in table 2. Because the output scale of a small-sized plant is only $\frac{1}{660}$th of a large-sized plant, it is no surprise the see many more small-sized plants in the all-small scenario and only a few large-sized plants in the all-large scenario.

Table 2. Plant Size Distributions under Different Structures

Scenario	No. small plants	No. medium plants	No. large plants	No. plants
Current	615	33	22	670
All-small	22,000	0	0	22,000
All-large	0	0	30	30

We consider various shutdown risks, including 5%, 10%, 20%, 30%, 40%, and 50%. The risk is common to all plants in a scenario and is independently and randomly realized. The risk is not set as a function of the plant size, because there is no evidence against this setup. For example, capacity reductions in beef slaughter plants during COVID-19 did not depend on plant sizes (Bina et al., 2021). Other supply-side risks such as fire outbreak and machinery breakdown could be higher for smaller plants due to their use of older buildings/facilities (Williams, 2018) or lower because of more careful supervision in daily operation. By imposing a common risk to all plants, we are able to isolate the effect of changing the structure on industry outputs and prices under a particular risk.

[3] Strictly speaking, the total output by 30 large plants is slightly lower under no risk compared with the current and all-small scenarios. Because the number of plants has to be an integer, 30 plants already give us an output level closest to the other two scenarios.

Given a scenario and a risk level, 1,000 simulations are conducted to generate equilibrium prices and outputs. At each iteration, a [0, 1] uniform random draw is taken for each plant. If the draw exceeds the assigned shutdown risk level (e.g., 0.3), the plant stays open, otherwise the plant closes and produces zero output. Once the risk is realized for each plant, industry output and prices and welfare measurements are re-computed for packing plants that remain open.

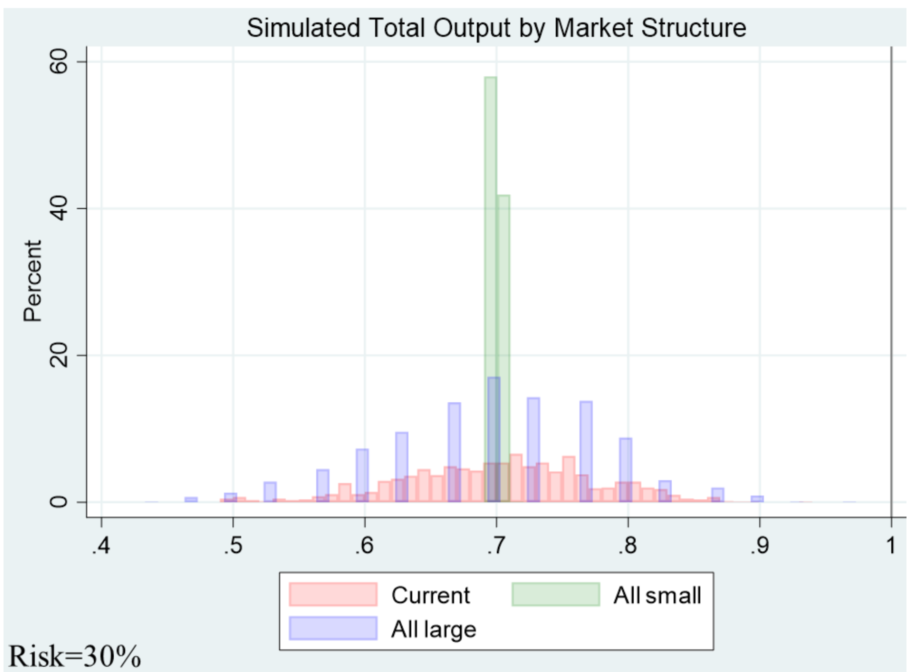
To judge the fitness of the model, we begin by comparing simulation outcomes from the current scenario to actual price and output changes witnessed during COVID-19, confirming that this scenario indeed captures key features of the U.S. beef industry. In April and May 2020, the U.S. beef packing sector experienced substantial supply-side disruptions due to slowdown and shutdown of packing plants. Daily number of federally inspected cattle processed fell 20-40% year-over-year for eight weeks (Lusk, Tonsor, and Schulz, 2021). From February to mid-May, the farm-to-wholesale price spread increased by over 250%. Our simulation outcomes depict a similar picture. When the risk of shutdown is 30%, the farm-to-wholesale price spread rises from 0.16 to 0.44, an increase of 179%. With a 40%-risk, the increase becomes 241%. The large increases in the price spread, however, do not mean an increase in packer profits. Our simulations show that the total profits of plants fall with a decreased processing capacity of the sector, as observed in the real world.

We proceed to compare the current horizontal structure to the two counter-factual structures. One general insight is that the new equilibrium prices and outputs after plant shutdowns have almost identical mean values, regardless of the structure. The structure matters only when we consider the variation in new equilibrium prices and outputs across the 1,000 iterations: there is much less variation in a diffuse sector than in more concentrated ones.

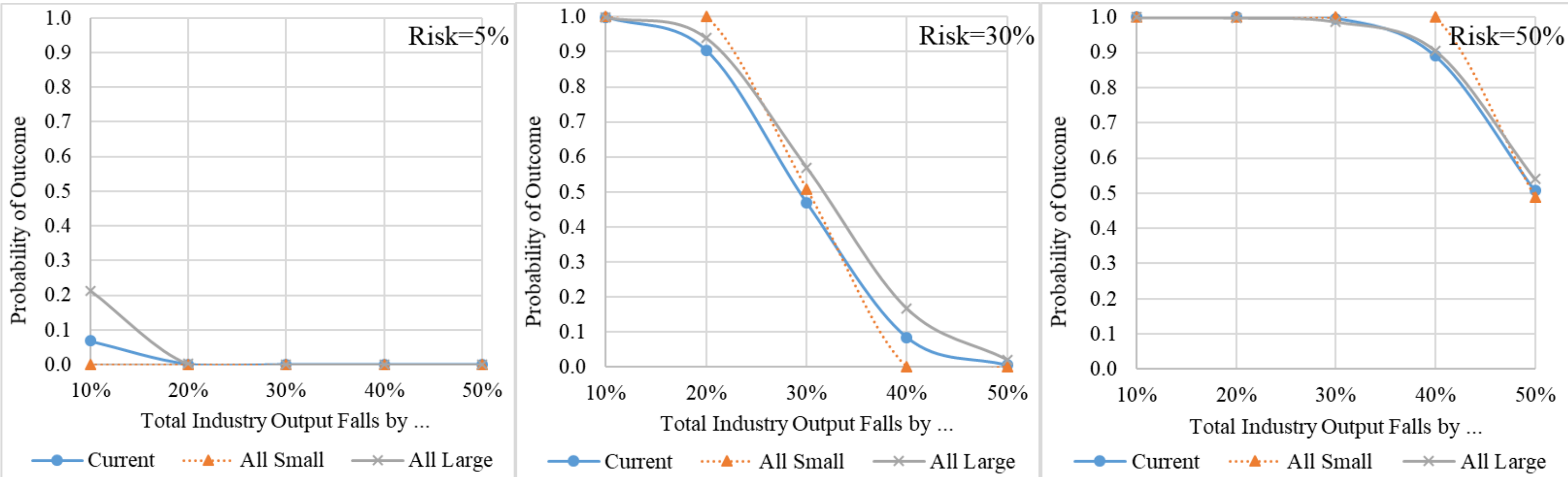
The intuition is straightforward and captured by panel (a) of figure 1. With a large number of small plants, outcomes from imposing random shocks always converge to the expected level. For example, if each plant faces a 30% chance of shutdown in the all-small scenario, approximately 30% of plants will close and, because all plants are the same small size, output will fall approximately 30% in every iteration. Therefore, its distribution of simulated outputs is highly concentrated around the mean of 0.70 (i.e., the green bars in the figure). With a small number of plants, however, a simulation outcome of imposing random shocks could vary widely around the expected level, particularly if a large plant happens to receive a “good” or “bad” draw in an iteration. The distribution of simulated outputs under the all-large scenario has wide tails or high variance (i.e., the blue bars in the figure). The current scenario generates outcomes that lie in between the two extreme structures.

Panel (b) of figure 1 shows the probability of avoiding different reductions (i.e., target levels of operation) in the sector’s total output given a shutdown risk and a horizontal structure. When the risk is small (e.g., 5%), the all-small scenario always outperforms the other two scenarios in achieving the lowest probability of experiencing any output reduction, and the all-large scenario is always the worst. When the risk level is medium (e.g., 30%), the all-small scenario outperforms only in achieving the lowest probability of experiencing large output reductions such as 40%+ (i.e., more than 40%) and 50%+. The current scenario performs the best regarding relatively small output reductions. When the risk level is high (e.g., 50%), the three scenarios perform equally in experiencing 10%+ and 20%+ reductions. The all-large scenario performs slightly better in avoiding 30%+ reductions. The current scenario outperforms regarding 40%+ reductions, while the all-small scenario remains the best in avoiding 50%+ reductions.

Given the patterns, we argue that the short-run resilience of a horizontal structure depends on the goal of a policy as well as the risk of shutdown. If the goal is to ensure a level of output close to the "normal" level (and thus food security), a relatively concentrated processing sector performs better than a more diffuse packing sector for a medium or large risk of plant shutdown, while a diffuse sector outperforms under a small risk. If the policy aims to ensure output does not fall below a minimal threshold, then the diffuse structure tends to outperform under all risk levels considered.



(a)



(b)

Figure 1. Simulated Industry Output under Different Risk Levels and Structures

Source: Author's simulation outcomes.

Note: In panel (a), the horizontal axis is the normalized simulated total output ranging from 0.4 to 1. The vertical axis is the percentage of 1,000 simulated cases that produce the corresponding output under a particular structure. In panel (b), the horizontal axis indicates the reduction in total industry output with "X%" meaning that "total output falls by more than X% compared with the risk-free output". The vertical axis measures the corresponding probability of experiencing a reduction in total output larger than X%. Plant outputs under risks are fixed at the risk-free levels.

Table 3 summarizes the mean farm-to-retail price spread under different horizontal structures and risk levels. The mean values under the three structures are almost the same and all increase with shutdown risk, but there is considerably more variation in the price spread across simulations in a less concentrated market. The price spread widens as shutdown risk increases, intuitively, because the retail price increases as the quantity of processed beef decreases and the farm price falls. Even in a perfectly competitive market (i.e., the all-small scenario), the price spread widens at the same rate as the other scenarios with an increasing shutdown risk.[4]

In the meantime, the profits made by packing plants drop. In the perfectly competitive scenario, of course, the packers never make profits by construction, and the packer profits remain at zero regardless of the risk. In the two other scenarios, the packing plants exercise some buyer and seller power. Their profits do not increase with the widening price spread because the increase in the spread is not due to packers' markups over retailers or markdowns over farmers. Instead, the increasing spread is driven by the loss of processing capacity. Marginal costs of processing increase considerably as the capacity falls, more than cancelling out any potential profits to packers from reducing industry-level outputs.

Worth noticing from table 3, consumer and producer (farmer) surpluses fall with an increasing shutdown risk. In expectation, the three scenarios lead to the same consumer and producer surpluses under a given risk. Total social welfare, which is the summation of consumer and farmer surpluses and packer profits, is the largest in the all-large scenario, thanks to the high cost efficiency of large-sized processing plants. The finding echoes prior studies such as Azaam and Schroeter (1995) who find that welfare losses from market power are more than offset by

[4] By construction of our model, the farm-to-wholesale price spread increases by the same increments as the farm-to-retail price spread because the marginal costs of retailing is fixed at $c^r = 0.42$.

higher cost efficiencies of large-sized packing plants. We revisit the evaluation of social welfare in section 4.3.

Table 3. Simulated Mean Values under Different Structures

Scenario	Risk=5%	Risk=10%	Risk=20%	Risk=30%	Risk=40%	Risk=50%
Price spread						
Current	0.622	0.671	0.762	0.856	0.951	1.045
All-small	0.623	0.670	0.764	0.858	0.952	1.046
All-large	0.624	0.671	0.765	0.859	0.950	1.042
Packer profits						
Current	0.023	0.021	0.019	0.017	0.014	0.012
All-small	0.000	0.000	0.000	0.000	0.000	0.000
All-large	0.030	0.028	0.025	0.022	0.019	0.016
CS						
Current	0.233	0.208	0.167	0.128	0.095	0.066
All-small	0.232	0.209	0.165	0.126	0.093	0.064
All-large	0.232	0.209	0.166	0.128	0.095	0.067
PS						
Current	0.192	0.172	0.137	0.106	0.078	0.054
All-small	0.191	0.172	0.136	0.104	0.076	0.053
All-large	0.191	0.172	0.136	0.105	0.078	0.056
Total welfare						
Current	0.448	0.402	0.323	0.251	0.187	0.133
All-small	0.424	0.381	0.301	0.230	0.169	0.118
All-large	0.453	0.409	0.327	0.255	0.192	0.139

Source: Authors' simulation outcomes.

Note: "Price spread" refers to the farm-to-retail price spread. "CS" means consumer surplus and "PS" means producer surplus. "Total welfare" equals the summation of consumer surplus, producer surplus, and packer profits.

Figure 2 summarizes changes in the marginal processing costs of small-sized, medium-sized, and large-sized plants in the current scenario. The mean increases are similar in the other two scenarios. Changes in the marginal processing costs for three size groups follow similar trends as the shutdown risk increases. Because the processing capacity of each plant is fixed in the short-run, the implied marginal costs increase with the decreasing total outputs as indicated by equation (9b). For example, when the average reduction in total outputs is 30%, the marginal costs of small, medium, and large plants increase by 180%, 189%, and 224%, respectively, relative to the risk-free level. The substantial costs increases imply a tight bottleneck in processing at the full capacity and also increased operational costs in a risky environment like COVID-19 (e.g., Lusk, Tonsor, and Schulz, 2021).[5]

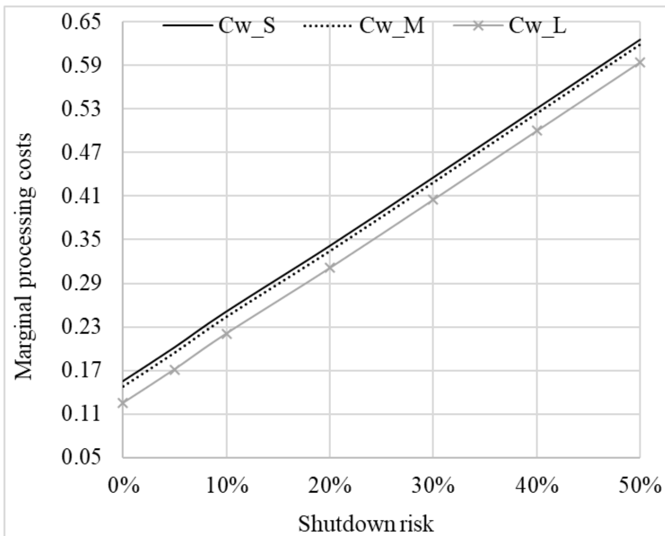


Figure 2. Marginal Processing Costs of Different Sized Plants under Risks

Source: Authors' simulation outcomes.

Note: The small, medium, and large sized plants are defined in the modeling section under the current structure. See table 1 for plant sizes. "Cw_S" refers to the marginal costs of processing for small-sized plants, "Cw_M" for medium-sized plants, and "Cw_L" for large-sized plants.

[5] Marginal costs of manufacturing rises substantially at a binding capacity constraint regardless of the commodity. See a recent example from the electricity industry in Texas. https://www.usnews.com/news/us/articles/2021-02-18/texas-power-consumers-to-pay-the-price-of-winter-storm

4.2 Sensitivity Analysis

We test the robustness of baseline simulation outcomes by considering alternative parameter values and assumptions. First, we relax the assumption of unit supply elasticity. According to the literature, the short-run supply of beef is likely to be quite low (see table A3). Letting ϵ^f be 0.8, 0.6, and 0.4, respectively, we re-run the simulations. The general patterns observed in the baseline stay unchanged.

Taking the cases where the shutdown risk is 30% as an example, figure 3 shows output reductions under less elastic supply. Again, the relative resilience of a horizontal structure depends on the goal of a policy. If the goal is to ensure a high level of output, a concentrated processing sector performs better than a more diffuse packing sector. If the goal is to ensure output does not fall below a minimal threshold, then the diffuse structure tends to outperform.

Worth noticing, with less elastic supply of cattle, the farm-gate price may fall negative if the shutdown risk is large. For instance, when $\epsilon^f = 0.4$ and the risk is 30%, P^f falls to -0.03 if the industry-level output drops by 43.2% from the risk-free level. A negative P^f implies that the farmers have to pay the processing plants for slaughtering their animals, when the processing capacity is very low. Consequently, the farm-to-retail price spread tends to be larger the more inelastic the cattle supply.

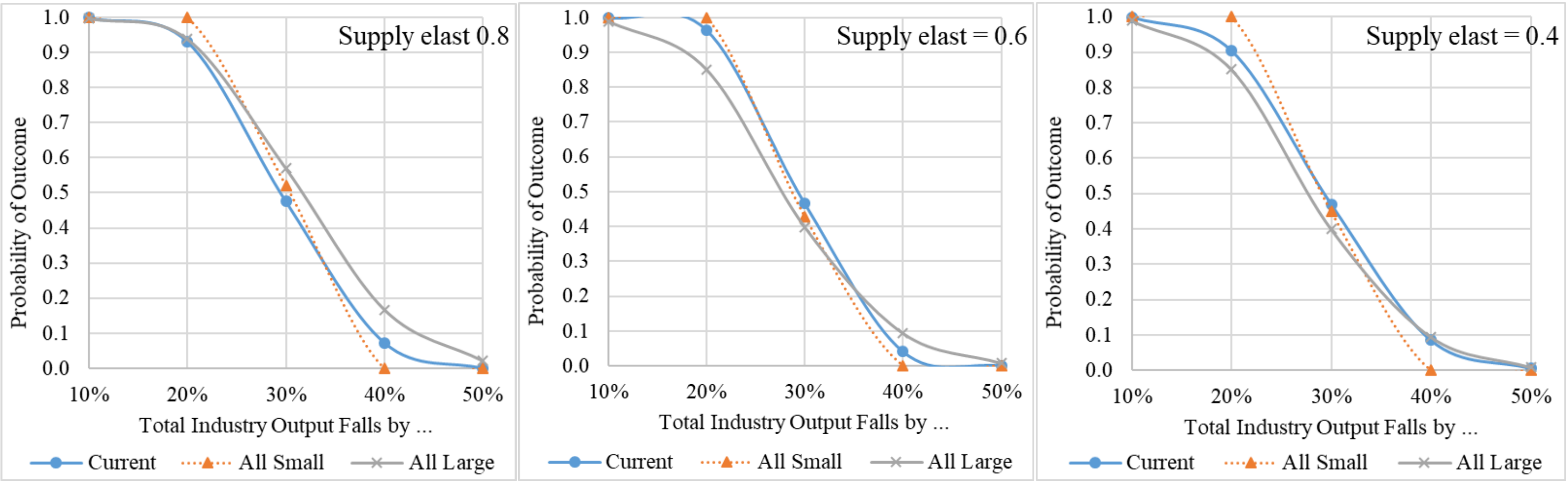


Figure 3. Simulated Industry Output under Different Risk Levels and Inelastic Cattle Supply

Source: Author’s simulation outcomes.

Note: same as figure 1.

Second, we consider simultaneous negative shocks on the demand and supply. For example, consumer demand may fall in a pandemic due to decreased visits to restaurants and reduced visits to grocery markets (Chetty et al., 2020), reductions in income, or the concern about getting the virus from consuming potentially contaminated products (McFadden et al., 2021). If the demand curve shifts inwards, we need to update the demand function as:

(10) $P^r = a' - \alpha Q$,

where $a' < a$. All other calculation steps remain the same.

Following this approach, we re-run the simulations by setting $a' = 0.95a$, $0.9a$, and $0.85a$, respectively. By construction, changes in the industry output follow the same patterns as shown in figure 1, because the supply would not be affected by a parallel shift in the demand curve. Only equilibrium prices at the farm gate and retail would be different. Specifically, the increase in P^r would be smaller if both demand and supply curves shift in. The change in P^f is not affected by a', leaving the price spread smaller with smaller a', *ceteris paribus* (see table 4).

Table 4. Mean Price spreads under Different Demand Shocks

Scenario	$a' = a$	$a' = 0.95a$	$a' = 0.9a$	$a' = 0.85a$
		Risk=30%		
Price spread				
Current	0.856	0.780	0.636	0.442
All-small	0.858	0.780	0.638	0.444
All-large	0.859	0.783	0.639	0.445

Source: Authors' simulation outcomes.

Note: "Price spread" refers to the farm-to-retail price spread.

Thirdly, we assume that demand remains unchanged, but allow operating plants to increase their outputs under supply-side shocks. Amid COVID-19 disruptions, for example, some packing plants made changes to fabrication and produced more whole cuts instead of small cuts or ran extra shifts on weekends in order to increase the total output with the same facilities and rising operational costs (Lusk, Tonsor, and Schulz, 2021). Being able to increase outputs beyond the full capacity is expected to add resilience in the supply chain.

In this simulation, we let plants that do not shutdown find new equilibrium outputs given higher marginal processing costs. With a shutdown risk of 30%, for example, we bring up the marginal costs of small-sized, medium-sized, and large-sized plants by 100%, 104.5%, and 120%, respectively. These cost increases are chosen to ensure that all plants achieve higher outputs, after some plants shut down, and that their output increases are not too large to be realistic nor so large that their size rankings change.

Given the cost increases listed here, the new equilibrium outputs of small-sized, medium-sized, and large-sized plants on average become 2.27, 1.07, and 1.19 times as large as their outputs under no risk, respectively. The average reduction in industry output is only 16.6% instead of 29.8% in the baseline, showing considerably more resilience in the beef supply chain. Besides, the probability of industry output falling by more than 20% drops to zero. Across all three scenarios, figure 4 shows that the decreases in industry outputs become smaller if we allow plants to increase outputs under supply shocks. The current and all-small structures result in almost identical outcomes, and both outperform the all-large structure.

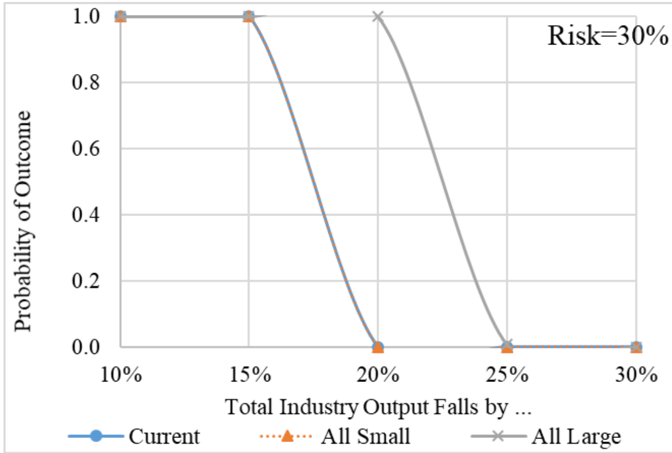


Figure 4. Simulated Industry Output with Adjustable Plant Outputs

Source: Author's simulation outcomes.

Note: same as figure 1. Plant equilibrium outputs increased after the supply shocks.

Lastly, we consider an alternative structure that is less extreme than all-large and all-small – some large-sized plants are replaced by small-sized plants, and the number of medium-sized plants remain unchanged. Specifically, we let there be 12 large-sized plants, 33 medium-sized plants, and 7,215 small-sized plants, which is a structure lying in-between the current and all-small structures. Figure 5 is directly comparable with panel (b) of figure 1. As expected, the simulation outcomes under this "in-between" structure are in-between outcomes from the current and all-small structures. Baseline insights remain unchanged.[6]

[6] We also change the way of imposing risks. Instead of assuming that we know the level of risk, we can draw the level of risk from a normal distribution. Then we generate multiple rounds of outcomes under an unknown risk. Again, the core insight that more concentrated structure leads to more variance in outcomes and similar mean stays robust.

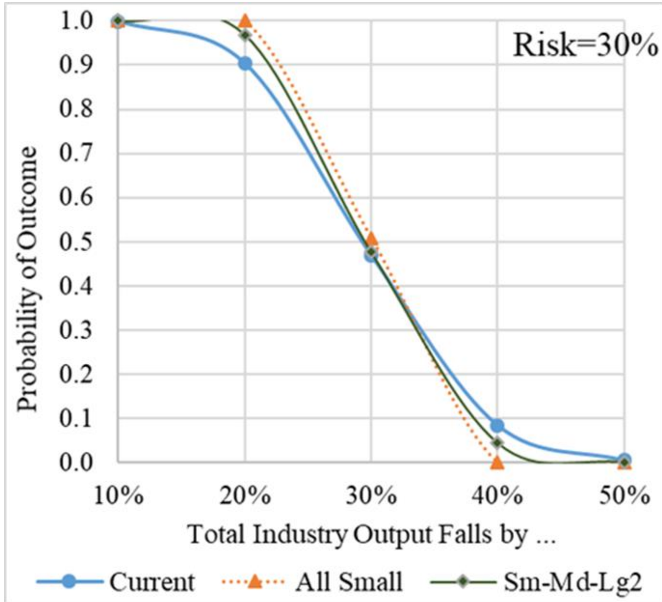


Figure 5. Simulated Industry Output under the Fourth Structure

Source: Author's simulation outcomes.

Note: same as figure 1. "Sm-Md_Lg2" refers to the structure with 12 large-sized plants, 33 medium-sized plants, and 7,215 small-sized plants.

4.3 Welfare Implications

Regarding social welfare, the criterion of welfare affects the ranking of alternative horizontal structures of meat packing. Table 3 indicates that, if a social planner only cares about the expected total welfare, the concentrated structure is preferred thanks to the economies of scale and lower marginal costs in processing. However, a social planner may care more than the mean welfare. In particular, the planner may want to avoid extreme losses in CS and PS. For instance, the planner may maximize a utility function that imposes a penalty if CS or PS falls below a lower bar (Holthausen, 1981).

To see how the alternative welfare criterion changes the ranking of various structures, we consider a linear loss avoidance utility function:

(10) $$\begin{cases} U(x) = x, \forall x > \underline{x} \\ U(x) = x - \kappa(\underline{x} - x), \forall x \leq \underline{x}, \end{cases}$$

where $x \in \{CS, PS\}$, $\underline{x}$ is the bar triggering penalty, and κ is the loss avoidance parameter. The larger is κ, the more loss averse is the planner. The total social welfare is the summation of $U = U(CS) + U(PS) + \Pi$ with Π being the collective profits of packers.

We consider a common risk of 30% as an example. Let the planner set $\underline{x}$ at 49% of the CS (PS) value without risk and maximizes the expected U. We find that the ranking of the three alternative structures varies with the magnitude of κ. Figure 6 indicates that, when the planner is not loss averse or κ is small, the all-large scenario outperforms due to efficiency gains discussed earlier. As the planner becomes sufficiently loss averse, the diffuse scenario starts to be preferred by being better at avoiding severe CS (PS) losses. Similarly, if the planner is risk averse and treats variance in the total welfare as disutility, the all-large scenario would tend to be less preferred than the other two structures.

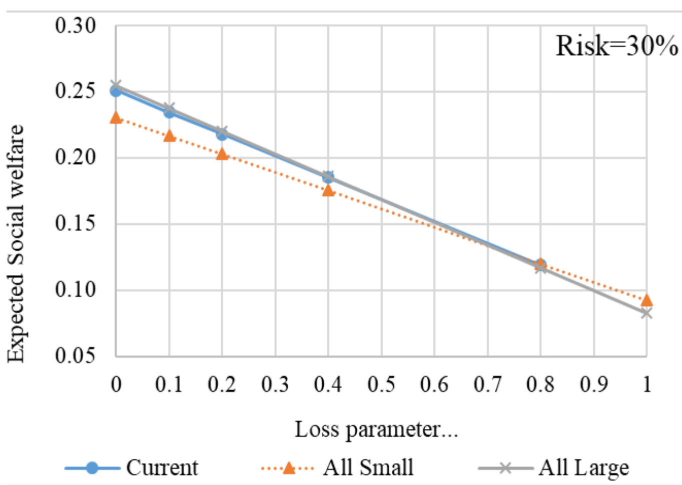


Figure 6. Simulated Social Welfare under Different Loss Avoidance Parameters

Source: Author's simulation outcomes.

Note: The vertical axis measures the expected social welfare. The horizontal axis measures the loss avoidance parameter, κ, in equation (10).

5. Policy Discussions

Several states have recently considered or adopted legislation to subsidize the introduction of small- or medium-sized meat packers. At the federal level, bills have been proposed to encourage more capital investments and allow small processors to access larger markets (e.g., Feedstuffs, 2020; Hagstrom, 2020). The implicit assumption behind such policy proposals is that they would result in more short-run resilience in the packing system faced with shocks like COVID-19. As the foregoing simulations suggest, however, a less concentrated packing system on average would not necessarily have produced outcomes much different than what was observed during April and May 2020, when cattle and hogs slaughter dropped by almost 40%. One, perhaps counterintuitive, simulation result is that total welfare is typically lower under a more diffuse packing sector because of the lost economies of scale.

In addition to policies aimed at promoting more small and medium-sized packers, a number of lawsuits have been levied at large meat packers, and a Justice Department investigation has been launched, following the packing plant shutdowns (e.g., Bunge and Kendall, 2020). Complaints tend to focus on the dramatic increase in the farm-to-wholesale price spread that occurred as a result of the plant shutdowns (Lusk, Tonsor, and Schulz, 2021). Our simulation provides insight into this phenomenon and the controversy surrounding it. In particular, regardless of the degree of concentration, the price spread rises when the industry is faced with an exogenous risk of shutdown. This finding is entirely consistent with the theory of marketing margins (Wohlgenant, 2001), and we show that widening price spreads result from disruptions to processing even if all packers are small-sized and there is no market power.

Moreover, even in scenarios where all packers are large, and packers earn profits, our simulations show that compared to the risk-free scenario, packer profits fall as price-spreads rise due to an exogenous shutdown risk. This seemingly counter-intuitive result arises because marginal costs also rise as exogenous shutdown risks bring down the packing capacity of the industry. Thus, our results suggest extreme caution in inferring market manipulation, market power, or packer profits from widening farm-to-wholesale or farm-to-retail price spreads.

These simulation outcomes reveal complex consequences of government and industry efforts aimed at increasing the resilience of the food supply chain through changing the horizontal structure. The consequences depend critically on the exogenous risk as well as the target level of industry output. Neither a diffuse nor a concentrated horizontal structure dominates. More comprehensive policy designs may be needed to add short-run resilience in the supply chain under supply-side disruptions. Though long-run resilience is not discussed in this article, biological cycles of livestock production, fixed investments, and other factors are likely to make the role of horizontal structure even more complex and imply even more difficulty in policy design. We leave the long-run resilience in U.S. meat supply chains for future research.

References

Aadland, David, and DeeVon Bailey. 2001. Short-Run Supply Responses in the U.S. Beef-Cattle Industry. *American Journal of Agricultural Economics* 83(4):826-39.

Azzam, Azzeddine M., and John R. Schroeter Jr. 1995. The Tradeoff between Oligopsony Power and Cost Efficiency in Horizontal Consolidation: An Example from Beef Packing. *American Journal of Agricultural Economics* 77(4):825-36.

Bina, Justin D., Glynn T. Tonsor, Lee L. Schulz, and William F. Hahn. 2021. Balancing Beef Processing Efficiency and Resiliency Post-COVID-19. Working Paper.

Bhamra, Ran, Samir Dani, and Kevin Burnard. 2011. Resilience: The Concept, A Literature Review and Future Directions. *International Journal of Production Research* 49(18): 5375-93.

Brester, Gary W., John M. Marsh, and Joseph A. Atwood. 2009. Evaluating the Farmer's-Share-of-the-Retail-Dollar Statistic. *Journal of Agricultural and Resource Economics* 34(2):213-36.

Bunge, Jacob, and Brent Kendall. 2020. Justice Department Issues Subpoenas to Beef-Processing Giants. *Wall Street Journal*. Available at: https://www.wsj.com/articles/justice-department-issues-subpoenas-to-beef-processing-giants-11591371745.

Bustillo, Ximena. 2020. Small Meat Processors Get Little Aid as Demand Grows. *Politico*. Available at: https://www.politico.com/news/2020/06/15/small-meat-processors-financial-aid-319822.

Dennis Dipietre, and Lance Mulberry. 2021. How Do the Profitability Puzzle Pieces Align for 2021? *Pork Business* https://www.porkbusiness.com/news/hog-production/how-do-profitability-puzzle-pieces-align-2021.

Feedstuffs. 2020. RAMP-UP Act Helps Meat Processors Upgrade Plants. Available at: https://www.feedstuffs.com/news/ramp-act-helps-meat-processors-upgrade-plants.

Hagstrom, Jerry. 2020. Small Packer Processing Bill Introduced in House. *Ag Policy Blog. DTN*. Available at: https://www.dtnpf.com/agriculture/web/ag/blogs/ag-policy-blog/blog-post/2020/09/30/small-packer-processing-bill-house.

Hahn, William. 2004. *Beef and Pork Values and Price Spreads Explained*. Livestock, Dairy, and Poultry Outlook No. (LDPM-11801) 30. Washington D.C.: US Department of Agriculture, Economic Research Service.

Hendrickson, Mary K. 2015. Resilience in a Concentrated and Consolidated Food System. *Journal of Environmental Studies and Sciences* 5(3):418-31.

Holthausen, Duncan M. 1981. A Risk-Return Model with Risk and Return Measured as Deviations from A Target Return. *American Economic Review* 71(1): 182-8.

Bina, Justin D., Glynn T. Tonsor, Lee L. Schulz, and William F. Hahn. 2021. Balancing Beef Processing Efficiency and Resilience Post-COVID-19. Working paper.

Koontz, Stephen R., and John D. Lawrence. 2010. Impacts of Alternative Marketing Agreement Cattle Procurement on Packer Costs, Gross Margins, and Profits: Evidence from Plant-Level Profit and Loss Data. *Agribusiness* 26(1):1-24.

Lusk, Jayson L., Glynn T. Tonsor, and Lee L. Schulz. 2021. Beef and Pork Marketing Margins and Price Spreads during COVID-19. *Applied Economic Perspectives and Policy* 43(1): 4-23.

MacDonald, James M., Michael E. Ollinger, Kenneth E. Nelson, and Charles R. Handy. 1999. *Consolidation in U.S. Meatpacking.* Washington D.C.: U.S. Department of Agriculture, Economic Research. Agricultural Economics Report no AER-785, March.

MacDonald, James M. 2003. Beef and Pork Packing Industries. *The Veterinary Clinics of North America. Food Animal Practice* 19(2):419-43.

MacDonald, James M., and Michael E. Ollinger. 2005. Technology, Labor Wars, and Producer Dynamics: Explaining Consolidation in Beefpacking. *American Journal of Agricultural Economics* 87(4):1020-33.

Marsh, John M. 2003. Impacts of Declining U.S. Retail Beef Demand on Farm-Level Beef Prices and Production. *American Journal of Agricultural Economics* 85(4):902-13.

McKendree, Melissa G.S., Tina L. Saitone, and K. Aleks Schaefer. 2020. Oligopsonistic Input Substitution in a Thin Market. *American Journal of Agricultural Economics* doi:10.1111/ajae.12159

Morrison Paul, Catherine J. 2001. Market and Cost Structure in the U.S. Beef Packing Industry: A Plant-Level Analysis. *American Journal of Agricultural Economics* 83(1):64-76.

National Agricultural Statistics Service (NASS). 2020. *Livestock Slaughter 2019 Summary*. U.S. Department of Agriculture, April.

Nickelsburg, Monica. 2020. The Pandemic Has the Potential to Finally Transform Meat Processing in the U.S. *Civil Eats.* Available at: https://civileats.com/2020/10/19/the-pandemic-has-the-potential-to-finally-transform-meat-processing-in-the-u-s/.

Perloff, Jeffrey M., Larry S. Karp, and Amos Golan. 2007. *Estimating Market Power and Strategies*. Cambridge University Press.

Pitt, David. 2021. USDA Unveils $500 Million Plan to Help Build More, Smaller Meat Processing Plants. *PBS*. Available at: https://www.pbs.org/newshour/economy/usda-unveils-500-million-plan-to-help-build-more-smaller-meat-processing-plants.

Ponomarov, Serhiy Y., and Mary C. Holcomb. 2009. Understanding the Concept of Supply Chain Resilience. *International Journal of Logistics Management* 20(1): 124-43.

Raper, Kellie Curry, Laura M. Cheney, and Meeta Punjabi. 2006. Regional Impacts of a U.S. Hog Slaughter Plant Closing: The Thorn Apple Valley Case. *Review of Agricultural Economics* 28(4):531-42.

Rotz, Sarah, and Evan D.G. Fraser. 2015. Resilience and the Industrial Food System: Analyzing the Impacts of Agricultural Industrialization on Food System Vulnerability. *Journal of Environmental Studies and Sciences* 5(3):459-73.

U.S. Department of Agriculture. 2020. *Boxed Beef & Fed Cattle Price Spread Investigation Report*. Agricultural Marketing Service (AMS). July.

U.S. Department of Agriculture. 2021. *Meat Price Spreads*. Available at: https://www.ers.usda.gov/data-products/meat-price-spreads/.

Williams, Cole. 2018. The Basics of Fire Insurance for Small Meat Plants. *The National Provioner*. Available at: https://www.provisioneronline.com/articles/106353-the-basics-of-fire-insurance-for-small-meat-plants.

Wohlgenant, Michael K. 2001. Marketing Margins: Empirical Analysis. *Handbook of Agricultural Economics* 1:933-70.

—— . 2013. Competition in the U.S. Meatpacking Industry. *Annual Review of Resource Economics* 5(1):1-12.

Appendix 1. Size Distribution of Processing Plants in the United States

Table A1 summarizes the distribution of plant sizes in the beef and pork processing sectors, respectively. Their horizontal structures are similar.

Table A1. Size Distributions of U.S. Meat Packing Plants

Size group	# plants	% plants	Head/year	Head/plant/year	% total output
Beef					
1-999	480	71.6%	163.2	340.0	0.5%
1,000-9,999	107	16.0%	261.5	2,443.9	0.8%
10,000-49,999	28	4.2%	604.9	21,603.6	1.8%
50,000-99,999	6	0.9%	483.0	80,500.0	1.5%
100,000-199,999	9	1.3%	1,270.7	141,188.9	3.8%
200,000-299,999	4	0.6%	1,018.8	254,700.0	3.1%
300,000-499,999	14	2.1%	5,554.3	396,735.7	16.8%
500,000-999,999	10	1.5%	6,394.2	639,420.0	19.3%
1,000,000+	12	1.8%	17,318.8	1,443,233.3	52.4%
All	670	100%	33069.4		100%
Pork					
1-999	396	64.0%	125.4	316.7	0.1%
1,000-9,999	123	19.9%	337.9	2,747.2	0.3%
10,000-99,999	39	6.3%	1,529.4	39,215.4	1.2%
100,000-249,999	18	2.9%	2,967.6	164,866.7	2.3%
250,000-499,999	7	1.1%	2,501.0	357,285.7	1.9%
500,000-999,999	3	0.5%	2,074.1	691,366.7	1.6%
1,000,000-1,999,999	6	1.0%	7,849.1	1,308,183.3	6.1%
2,000,000-2,999,999	12	1.9%	31,794.8	2,649,566.7	24.6%
3,000,000+	15	2.5%	80,031.5	5,335,433.3	61.9%
All	619	100%	129210.8		100%

Source: National Agricultural Statistics Service (2020).

Note: The column of “head/year” shows the number of animals slaughtered by plants in the size group in a year and uses the unit of 1,000 head.

Appendix 2. Elasticities of U.S. Beef Demand and Cattle Supply

The two tables below summarizes estimates of beef demand and cattle supply in the United States from recent empirical studies.

Table A2: Demand Elasticities of U.S. Beef in Recent Studies

Source	Data period	Data frequency/type	Demand elasticities	Notes
Lusk and Tonsor (2016)	2013-14	Monthly, Choice experiment	-1.959	Low income, Ground beef, Price increase
			-1.834	Middle income, Ground beef, Price increase
			-1.703	High income, Ground beef, Price increase
			-2.511	Low income, Ground beef, Price decrease
			-2.377	Middle income, Ground beef, Price decrease
			-2.075	High income, Ground beef, Price decrease
			-1.738	Low income, Steak, Price increase
			-1.836	Middle income, Steak, Price increase
			-1.674	High income, Steak, Price increase
			-2.625	Low income, Steak, Price decrease
			-2.606	Middle income, Steak, Price decrease
			-2.061	High income, Steak, Price decrease
Mutondo and Henneberry (2007)	1995-2005	Quarterly, USDA/ERS, USDA/FAS	-0.712	U.S. grain-fed beef, Uncompensated
			-0.507	U.S. grass-fed beef, Uncompensated

Table A2 (continued)

Source	Data period	Data frequency/type	Demand elasticities	Notes
Shang and Tonsor (2017)	2009-14	Monthly, Scanner Data	-0.998	Beef, Total US
		from IRI	-0.830	Ground beef, Total US
		FreshLook Perishable Service	-0.700	Other beef, Total US
Taylor and Tonsor (2013)	2007-11	Monthly, Scanner Data	-1.274	Beef, Uncompensated, Meat separable
		collected by Fresh Look	-0.944	Beef, Uncompensated, Food separable
		Marketing Group	-2.011	Beef loin, Uncompensated, Meat separable
			-1.242	Ground beef, Uncompensated, Meat separable
			-1.254	Other beef, Uncompensated, Meat separable
Tonsor et al. (2018)	1970-2017	Quarterly, USDA/ERS	-0.479	Beef, All-Fresh, 1988-2017
			-0.645	Beef, All-Fresh, 1988-2007
			-0.450	Beef, All-Fresh, 2008-2017
			-0.593	Beef, Choice, 1970-2017
			-0.490	Beef, Choice, 1988-2017
			-0.594	Beef, Choice, 1970-1994
			-0.468	Beef, Choice, 1995-2017
Tonsor et al. (2010)	1982-2007	Quarterly, USDA/ERS	-0.420	Beef, Compensated
Tonsor and Olynk (2011)	1982-2008	Quarterly, USDA/ERS	-0.493	Beef, Compensated

Lusk, Jayson L., and Glynn T. Tonsor. 2016. How Meat Demand Elasticities Vary with Price, Income, and Product Category. *Applied Economic Perspectives and Policy* 38(4):673-711.

Mutondo, Joao E., and Shida Rastegari Henneberry. 2007. A Source-Differentiated Analysis of U.S. Meat Demand. *Journal of Agricultural and Resource Economics* 32(3):515-33.

Shang, Xia, and Glynn T. Tonsor. 2017. Food Safety Recall Effects across Meat Products and Regions. *Food Policy* 69:145-53.

Taylor, Mykel R., and Glynn T. Tonsor. 2013. Revealed Demand for Country-of-Origin Labeling of Meat in the United States. *Journal of Agricultural and Resource Economics* 38(2):235-47.

Tonsor, Glynn T., Jayson L. Lusk, and Ted C. Schroeder. 2018. Assessing Beef Demand Determinants. Report for Cattlemen's Beef Board.

Tonsor, Glynn T., James R. Mintert, and Ted C. Schroeder. 2010. U.S. Meat Demand: Household Dynamics and Media Information Impacts. *Journal of Agricultural and Resource Economics* 35(1):1-17.

Tonsor, Glynn T., and Nicole J. Olynk. 2011. Impacts of Animal Well-Being and Welfare Media on Meat Demand. *Journal of Agricultural Economics* 62(1):59-72.

Table A3: Supply Elasticities of U.S. Cattle in Recent Studies

Source	Data period	Data frequency/type	Supply elasticities	Note for demand elasticities
Marsh (2003)	1970-99	Annual, USDA's red meats yearbook	0.26	Short-run elasticity of slaughter supply
			0.59	Long-run elasticity of slaughter supply
			0.22	Short-run price elasticity of feeder supply
			2.82	Long-run price elasticity of feeder supply
McKendree (2020)	1996-2016	Quarterly, Livestock marketing information center (LMIC)	0.10	Short-run fed cattle supply elasticity
			0.24	Long-run fed cattle supply elasticity
			0.17	Short-run feeder cattle supply elasticity
			0.24	Long-run feeder cattle supply elasticity
Suh and Moss (2017)	1981-2011	Annual, FAOSTAT, USDA/ERS	0.12	Supply elasticity of cattle

Marsh, John M. 2003. Impacts of Declining U.S. Retail Beef Demand on Farm-Level Beef Prices and Production. *American Journal of Agricultural Economics* 85(4):902-13.

McKendree, Melissa GS, Glynn T. Tonsor, Ted C. Schroeder, and Nathan P. Hendricks. 2020. Impacts of Retail and Export Demand on United States Cattle Producers. *American Journal of Agricultural Economics* 102(3):866-83.

Suh, Dong Hee, and Charles B. Moss. 2017. Decompositions of Corn Price Effects: Implications for Feed Grain Demand and Livestock Supply. *Agricultural Economics* 48(4):491-500.