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8 Concentration and Resilience in the US Meat Supply Chains

Meilin Ma and Jayson L. Lusk

8.1 Introduction

Concentration in the US 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 percent of all plants, were responsible for 71.7 percent of federal inspected cattle processing in the US (National Agricultural Statistics Service or NASS 2020). Pork packing is similarly concentrated with the largest 15 plants, representing only 2.5 percent of all plants, responsible for 61.9 percent of all federally inspected hogs slaughtered (see appendix A). 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 percent of the total US processing capacity, caused a spike in the farm-to-retail price spread and led to law-

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suits 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 percent 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, Dani, and Burnard 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 US 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 US 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 reinforce Brester, Marsh, and Atwood's (2009) results that price spreads, in isolation, are uninformative as they relate to market power. A few recent papers have explored the market impacts that occur when a firm decides to close 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 8.2, 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 8.3. 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 US beef packing in 2019.

In section 8.4, 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 percent, 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 percent 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 percent 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 8.5, 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 Azzam and Schroeter Jr. (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 8.4.3).

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 meat packing 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.

8.2 Conceptual Model

Given heterogeneity in size of processors in the US 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 processing at

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.

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 counterfactual structures of the meat packing sector.

Let there be n processing plants of different sizes. The plants are denoted by $i \in \{1, 2, 3, \ldots n\}$. 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):

$$P^r = D(Q^r | X), \tag{1a}$$

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

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:

$$P^f = S(Q^f | Y), \tag{1c}$$

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 $Q^r = Q^w = Q^f = Q = \Sigma_n q_i$ 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:

$$C_i^w = c_i^w q_i + P^f(Q) q_i, \tag{2}$$

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:

$$\pi_i^w = (D(Q | X) - c^r) q_i - [c_i^w + P^f(Q | Y)] q_i. \tag{3}$$

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

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

where $\xi_i^w = (\partial Q / \partial q_i)(q_i / Q) \in [0,1]$ 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 1.0, the more market power exercised by the processing plant.

Under Cournot competition, $\xi_i^w = (\partial Q / \partial q_i)(q_i / Q) = [(\partial Q / Q) / (\partial q_i / Q_i)] = s_i = \theta_i^f$, meaning that the market power parameter of a processor equals its output share in the market.[2] As illustrated in section 8.3, 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 percent, implying limited exercise of market power in the processing sector.

8.3 Parameterization

To apply this framework to the US 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 US as the benchmark to characterize the risk-free horizontal structure. The pork packing sector has a similar structure.

As detailed in appendix A, 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 percent of all plants but contribute only 3.1 percent 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 percent of all plants and contribute 25.2 percent of the total output. On average, their annual output is 252.3 thousand head per plant. Finally, 3.3 percent of the plants slaughter over half million head per year and contribute 71.7 percent 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.

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 $\partial Q / \partial q_i$ be larger than 1. That is, when a plant changes its output levels, other plants 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.

8.3.1 Analytical Solutions

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

(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 can 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 $\alpha = 1/\eta^r$, $\beta = f/\varepsilon^f$, $a = 1 + 1/\eta^r$, 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 $(\partial Q / \partial q_i)(q_i / Q)$ 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 $\overline{c^w} = \sum_i^n c_i^w / n$ 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) $$PS = \frac{(P^{f*} - b)Q^*}{2}, \text{ and}$$

(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). Rearranging 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' active plants in the sector. In the short run, the remaining n' plants are unable to produce more than the initial equilibrium output, q_i^*, because of the fixed production capacity. Thus, the new total quantity processed is:

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

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, we consider an *implied* c_i^w that makes the initial outputs equilibrium outputs with n' active plants. The implied processing marginal cost reflects additional costs with producing just beyond the capacity and additional costs in a risky environment (e.g., sanitation and social distancing). It is higher than the initial c_i^w and equals:

(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.

8.3.2 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 US-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 table 8B.1. 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 US (see table 8B.2 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 1.0 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 1.0, 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 8.4.2, 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 percent 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 table 8A.1). 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 8.1.

8.4 Simulation Results

The calibrated model is flexible in considering various horizontal structures of the US 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.

Table 8.1 **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

Table 8.2 **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

8.4.1 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 8.2. Because the output scale of a small-sized plant is only 1/660th 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.

We consider various shutdown risks, including 5 percent, 10 percent, 20 percent, 30 percent, 40 percent, and 50 percent. 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

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.

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.

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 recomputed 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 US beef industry. In April and May 2020, the US 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 percent 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 percent. Our simulation outcomes depict a similar picture. When the risk of shutdown is 30 percent, the farm-to-wholesale price spread rises from 0.16 to 0.44, an increase of 179 percent. With a 40 percent risk, the increase becomes 241 percent. The large increases in the price spread, however, do not mean an increase in packer profits because the price spread increases as much in a competitive-market setup as under imperfect competition.

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 8.1. 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 percent chance of shutdown in the all-small scenario, approximately 30 percent of plants will close and, because all plants are the same small size, output will fall approximately 30 percent in every iteration. Therefore, its distribution of simulated outputs is highly concentrated around the mean of

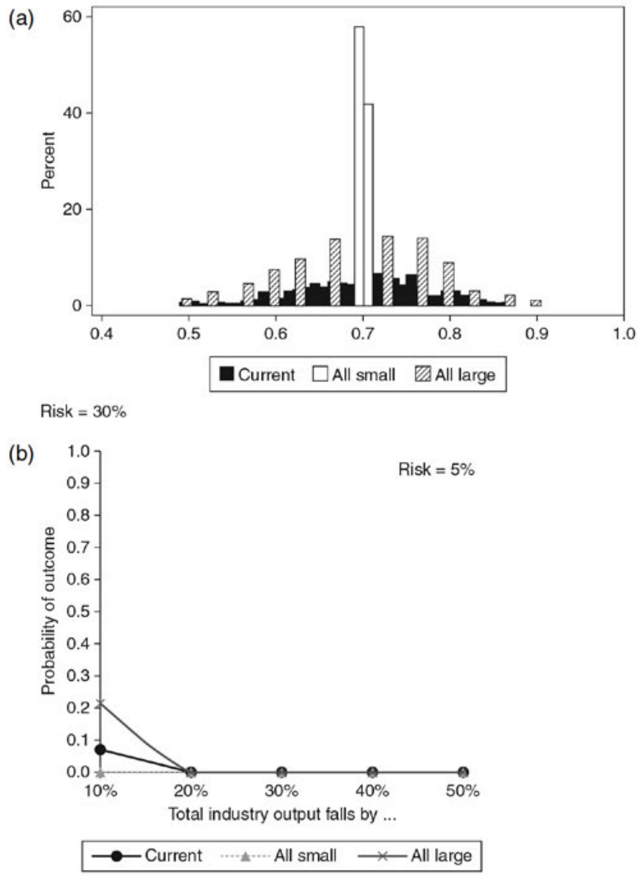

Figure 8.1 Simulated industry output under different risk levels and structures

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 panels (b) (c) (d), 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.

Source: Author's simulation outcomes.

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 8.1 shows the probability of avoiding different reductions (i.e., target levels of operation) in the sector's total output given a

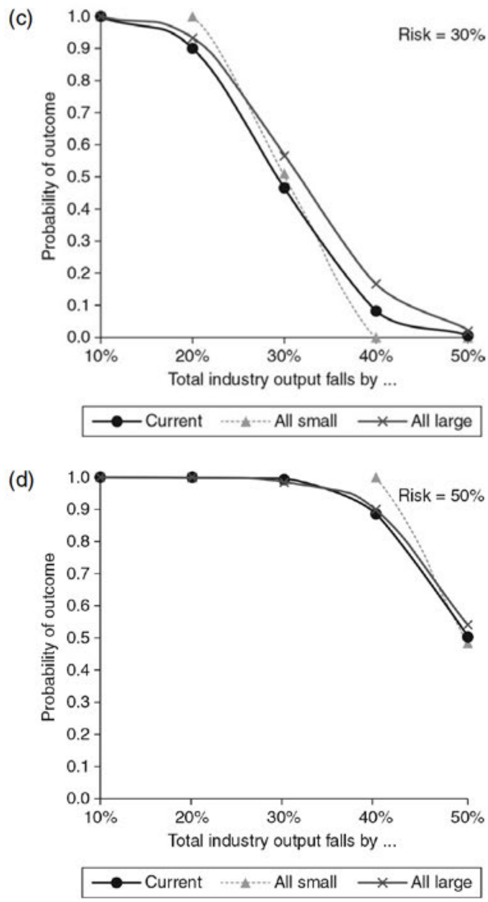

Figure 8.1 (continued)

shutdown risk and a horizontal structure. When the risk is small (e.g., 5 percent), 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 percent), the all-small scenario outperforms only in achieving the lowest probability of experiencing large output reductions such as 40 percent+ (i.e., more than 40 percent) and 50 percent+. The current scenario performs the best regarding relatively small output reductions. When the risk level is high (e.g., 50 percent), the three scenarios perform equally in experiencing 10 percent+ and 20 percent+ reductions. The all-large scenario performs slightly better in avoiding 30 percent+ reductions. The current scenario outperforms regarding 40 percent+ reductions, while the all-small scenario remains the best in avoiding 50 percent+ reductions.

Given the patterns, we argue that the short-run resilience of a horizontal

Table 8.3 **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

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.

Source: Authors' simulation outcomes.

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.

Table 8.3 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]

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 are fixed at $c^r = 0.42$.

In the meantime, the profits made by packing plants drop given the implied marginal costs. 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 of shutdown plants. Implied marginal costs of processing increase considerably as the industry's total capacity falls, more than canceling out any potential profits to packers from reducing industry-level outputs. If the actual marginal costs do not increase as much, of course, processor profits could increase after shutdowns, but still less than what the increased price spread would suggest.

Worth noticing from table 8.3, 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 Azzam and Schroeter Jr. (1995), who find that welfare losses from market power are more than offset by higher cost efficiencies of large-sized packing plants. We revisit the evaluation of social welfare in section 8.4.3.

Figure 8.2 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 implied 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 percdent, the implied marginal costs of small, medium, and large plants increase by 180 percent, 189 percent, and 224 percent, respectively, relative to the risk-free level. The substantial cost increases imply a tight bottleneck in processing at the (near) full capacity and some increased operational costs in a risky environment like COVID-19 (e.g., Lusk, Tonsor, and Schulz 2021).[5]

8.4.2 Sensitivity Analysis

We test the robustness of baseline simulation outcomes by considering alternative parameter values and assumptions. First, we relax the assumption

5. Marginal costs of manufacturing rise 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.

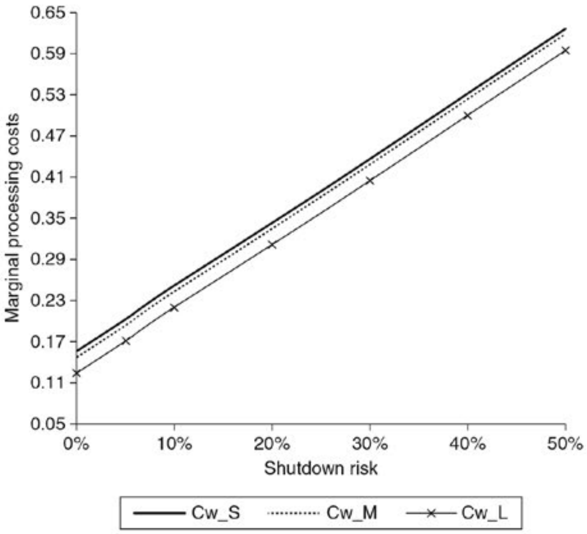

Figure 8.2 Marginal processing costs of different sized plants under risks

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.

Source: Authors' simulation outcomes.

of unit supply elasticity. According to the literature, the short-run supply of beef is likely to be quite low (see table 8B.2). Letting ε^f be 0.8, 0.6, and 0.4, respectively, we rerun the simulations. The general patterns observed in the baseline stay unchanged. Using smaller demand elasticity values makes no significant changes in simulation outcomes, either.

Taking the cases where the shutdown risk is 30 percent as an example, figure 8.3 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 $\varepsilon^f = 0.4$ and the risk is 30 percent, P^f falls to –0.03 if the industry-level output drops by 43.2 percent from the risk-free level. A negative P^f implies that the farmers must 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.

Second, we consider simultaneous negative shocks on the demand and

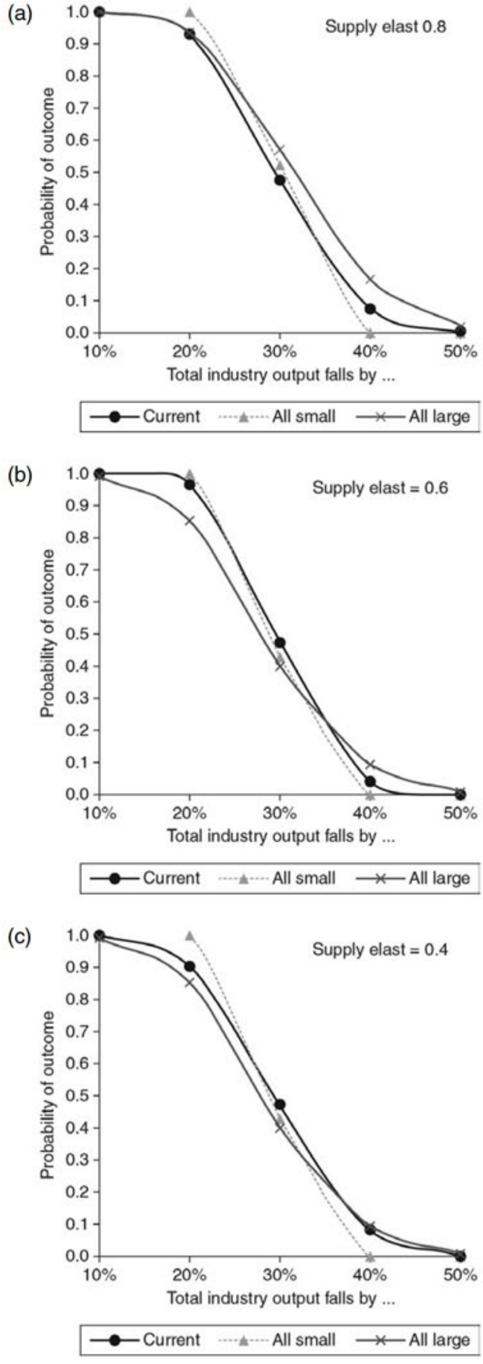

Figure 8.3 Simulated industry output under different risk levels and inelastic cattle supply

Note: same as figure 8.1.

Source: Author's simulation outcomes.

Table 8.4 **Mean price spreads under different demand shocks**

	Risk = 30%			
Scenario	$a' = a$	$a' = 0.95a$	$a' = 0.9a$	$a' = 0.85a$
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

Note: "Price spread" refers to the farm-to-retail price spread.
Source: Authors' simulation outcomes.

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:

$$P^r = a' - \alpha Q, \tag{10}$$

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

Following this approach, we rerun 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 8.1, 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', with other conditions remaining the same (see table 8.4).

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 shut down find new equilibrium outputs given higher marginal processing costs. With a shutdown risk of 30 percent, for example, we bring up the marginal costs of small-sized, medium-sized, and large-sized plants by 100 percent, 104.5 percent, and 120 percent, 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 or so large that their size rankings change.

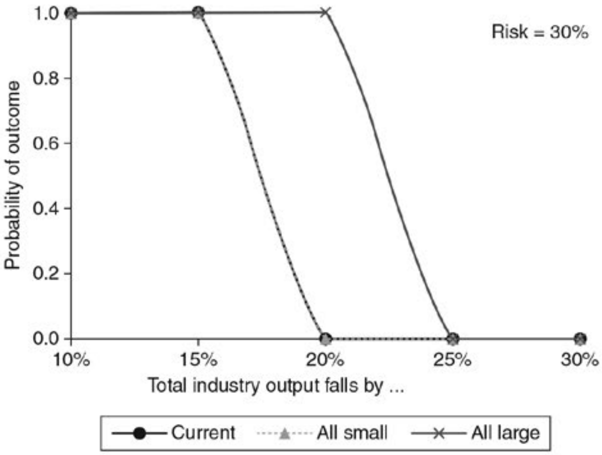

Figure 8.4 Simulated industry output with adjustable plant outputs
Note: same as figure 8.1. Plant equilibrium outputs increased after the supply shocks.
Source: Author's simulation outcomes.

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 percent instead of 29.8 percent in the baseline, showing considerably more resilience in the beef supply chain. Besides, the probability of industry output falling by more than 20 percent drops to zero. Across all three scenarios, figure 8.4 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.

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 8.5 is directly comparable with panel (b) of figure 8.1. 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.

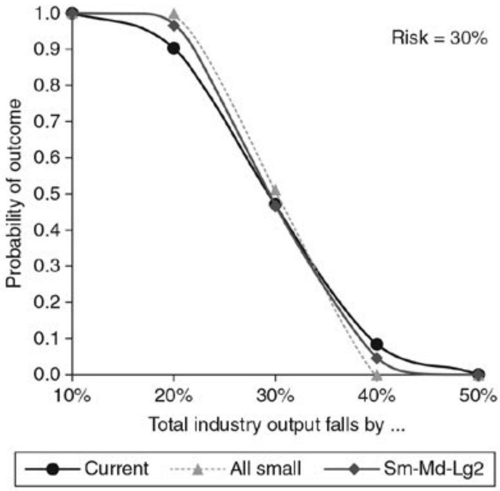

Figure 8.5 Simulated industry output under the fourth structure

Note: same as figure 8.1. "Sm-Md_Lg2" refers to the structure with 12 large-sized plants, 33 medium-sized plants, and 7,215 small-sized plants.

Source: Author's simulation outcomes.

8.4.3 Welfare Implications

Regarding social welfare, the criterion of welfare affects the ranking of alternative horizontal structures of meat packing. Table 8.3 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:

$$(11) \qquad \begin{cases} U(x) = x, \forall x > \underline{x} \\ U(x) = x - \kappa(\underline{x} - x), \forall x \leq \underline{x}, \end{cases}$$

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 percent as an example. Let the planner set $\underline{x}$ at 49 percent of the CS (PS) value without risk and maximizes the expected U. We find that the ranking of the three alternative structures varies

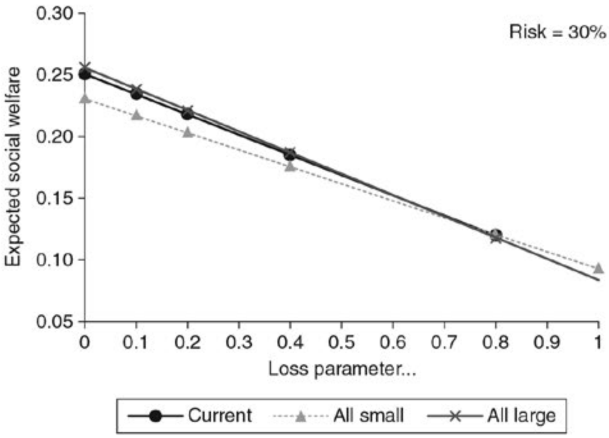

Figure 8.6 Simulated social welfare under different loss avoidance parameters
Note: The vertical axis measures the expected social welfare. The horizontal axis measures the loss avoidance parameter, κ, in equation (11).
Source: Author's simulation outcomes.

with the magnitude of κ. Figure 8.6 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.

8.5 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 hog slaughter dropped by almost 40 percent. 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.

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 US meat supply chains for future research.

Appendix A

Size Distribution of Processing Plants in the US

Table 8A.1 summarizes the distribution of plant sizes in the beef and pork processing sectors, respectively. Their horizontal structures are similar.

Table 8A.1 **Size distributions of US 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%

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.

Source: National Agricultural Statistics Service (2020).

Appendix B
Elasticities of US Beef Demand and Cattle Supply

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

Table 8B.1 Demand elasticities of US 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
Shang and Tonsor (2017)	2009–14	Monthly, Scanner Data from IRI FreshLook Perishable Service	−0.998	Beef, Total US
			−0.830	Ground beef, Total US
			−0.700	Other beef, Total US
Taylor and Tonsor (2013)	2007–11	Monthly, Scanner Data collected by Fresh Look Marketing Group	−1.274	Beef, Uncompensated, Meat separable
			−0.944	Beef, Uncompensated, Food separable
			−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

Table 8B.2 **Supply elasticities of US 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

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