Market Structure and Resilience of Food Supply Chains Under Extreme Events*

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Abstract

Recent extreme events and the disruptions they caused have made food supply chain resilience a key topic for researchers and policymakers. Several policy responses have been proposed with the goal of improving supply-chain resilience. This paper provides input into these discussions by evaluating the efficiency and resilience properties of the leading policy proposals. We develop a conceptual model of a prototype agricultural supply chain, parameterize the model based on current data and results from the empirical literature, and conduct simulations to assess the impacts on resilience and economic welfare of four key policy proposals: (i) intensified antitrust enforcement to improve market competition, (ii) subsidization of entry of additional processing capacity, (iii) prevention of price spikes through anti-price-gouging laws, and (iv) diversification of production and processing across multiple regions. Results show that some of the policies have potential to improve supply-chain resilience, but their impacts depend importantly on the existing market structure, and resilience gains often come at the cost of reduced efficiency and market surplus.

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JEL Codes: L13, L66, Q13, Q18

1 Introduction

Food supply chains have experienced severe disruptions in recent years, first due to the COVID-19 pandemic and then due to the conflict between Russia and Ukraine. These disruptions have motivated researchers and policymakers to assess the resiliency of food supply chains to extreme shocks and to search for policies to make them more robust to such events in the future (United Nations Food and Agriculture Organization, 2021; U.S. Department of Agriculture, 2022).

Extreme shocks to food systems can emanate from a variety of sources, including pandemics, geopolitical conflicts, and natural disasters. A key element linking possible extreme events is that they are likely to simultaneously impact food supply chains at successive stages. The COVID-19 pandemic, for example, caused short-run retail demand shocks for key staples, as consumers attempted to stockpile goods amidst fears of looming shortages, while the upstream production and processing stages experienced bottlenecks and reduced production due to processing plant shutdowns and inability to harvest some crops due to labor shortages (Martinez, Maples, and Benavidez, 2020; Lusk and Chandra, 2021).

The recent experiences have made building more resilient food supply chains that adapt quickly in the presence of extreme events a clear policy goal for much of the world. US policymakers have already introduced several measures intended to enhance the resilience of US food supply chains. They include intensified enforcement of competition laws, subsidizing entry of new processing firms, outlawing profiteering or "price-gouging" in response to severe market disruptions, and supporting geographic diversification of food systems. This paper seeks to evaluate the impacts of each of these policy interventions. Although substantial recent work has indicated the qualitative value of more resilient food supply chains, considerable debate remains regarding the optimal policy responses (Tukamuhabwa et al., 2015; Jiang, Rigobon, and Rigobon, 2021) and the implications for stakeholders along the supply chain (Davis, Downs, and Gephart, 2021).

Food supply chains have evolved through the quest for production efficiency and cost savings, but the common perception is that the most efficient supply chain structures may be the least resilient (Viswanadham and Kameshwaran, 2013; Hobbs, 2021; U.S. Department of Agriculture, 2022),[1] and, thus, strategies to enhance resilience may reduce efficiency of supply chain operations during normal times. To date, this possible resilience-efficiency trade-off has been discussed (Hobbs, 2021; Lusk, Tonsor, and Schulz, 2021), but has not been subjected to rigorous analysis nor quantified. Providing this input to policymakers is a key focus of our paper. Although we study policies that have been adopted or discussed in the US and calibrate the model to US data, we expect that our results will have relevance for other economies grappling with supply chain resilience issues.

We develop a flexible model of a prototype food supply chain, which allows US to express key trade-offs between efficiency and resilience under a broad set of extreme shocks and forms of market competition. Ability to depict alternative competition scenarios is a key consideration because market concentration and intermediaries' market power have been cited repeatedly by policymakers as factors that inhibit supply chain resilience (The White House, 2022; U.S. Department of Agriculture, 2022).

A key innovation of our model relative to others is that we incorporate explicitly that extreme shocks will impact supply chains simultaneously at multiple stages, as was true with the onset of the COVID-19 pandemic. We simulate the correlated nature of market shocks by drawing shock variables for the vertical stages of the supply chain—farm production, processing and retailing, and consumption—from a multi-variate joint distribution. We show that shocks to farm supply, consumer demand, and processing capacity are more disruptive the greater their correlation.

We calibrate the model based on contemporary data and recent empirical research for the US to represent prototype supply chains for key staples. We then utilize Monte-Carlo simulations to examine the welfare impacts for supply chain participants of different extreme

[1]For example, the USDA (U.S. Department of Agriculture, 2022) begins its report on agricultural competition by asserting "the pandemic exposed the risks and dangers created by many of today's production systems, which value hyper-efficiency over competition and resiliency" (p.2).

events under alternative supply chain structures and policy responses. Market efficiency of alternative supply chain structures is measured in terms of the mean economic surplus they generate across simulated market outcomes, while market resilience is measured in terms of the relative variance (coefficient of variation) under a large number of simulated shocks.

We utilize the calibrated model and simulation framework to study four policy proposals that have emerged in the resilience debate. First, we investigate the role of concentration and market power in the processing/retailing sector on resilience of supply chains in response to extreme shocks. On January 3, 2022, the Biden Administration announced plans for stricter enforcement of antitrust laws in the meatpacking industries. In addition, legislation known as the Meat and Poultry Special Investigator Act of 2022 has been introduced in the US Congress to give the US Department of Agriculture (USDA) authority to investigate competition issues in the meat and poultry industries. USDA itself has announced plans to partner with the US Department of Justice to enforce antitrust laws vigorously and to also step up its own enforcement of competition under the Packers and Stockyards Act (U.S. Department of Agriculture, 2022). Market power exercised by intermediaries is well understood to raise prices to consumers and depress prices received by farmers, but the impacts of market power on supply chain resilience are not well understood.

Second, given a baseline level of market power for market intermediaries, we study the impact of entry into the processing sector on market efficiency and resilience in the event of extreme shocks. As noted, subsidization of entry into meat processing is a key policy response being implemented in the US. Entry of processors spreads the shutdown risk across a greater number of plants and may reduce intermediaries' market power, but more processing facilities implies lower throughput per plant, generating higher costs in the presence of scale economies.

Third, we study the ramifications of price controls imposed along the supply chain in response to significant market shocks. These policies take the form of anti-price-gouging laws, or *ad hoc* price controls imposed by politicians under emergency authority. While these price limits impede intermediaries' exercise of market power and prevent extreme price shocks to consumers, they also may exacerbate shortages of products and limit market participants' abilities to adapt through a price mechanism to changing market conditions. We show that the impact of such price controls depends importantly on the competitive conditions of markets where they are imposed. In settings where intermediaries' exercise significant market power, price caps can cause higher output and economic surplus compared to the flexible-price case.

Fourth, we study whether more geographically dispersed production enhances resilience. Production of many agricultural commodities in the US has become highly specialized geographically, which has undoubtedly caused efficiency gains as regions produce according to their comparative advantage. Proponents of more diverse and localized food production systems argue that spatial concentration leaves the food supply chain vulnerable to devastating shocks that impact an entire production region and that local food systems are more nimble and resilient (Thilmany et al., 2021; Raj, Brinkley, and Ulimwengu, 2022). Our simulations illustrate the trade-off between reduced volatility due to more dispersed production risk, and reduced production efficiency and market surplus associated with geographically dispersed production systems.

Overall, we find that, while some of these policies can reduce relative volatility of welfare outcome for farmers and consumers, their impacts on resilience and efficiency depend critically on the structure and competitive conditions in the market. Policies aimed at increasing resilience must carefully assess the probabilistic nature of extreme events and the related efficiency trade-offs. This paper facilitates these discussions by providing a quantitative framework that enables the resilience-efficiency trade-offs of the major policy proposals to be assessed.

2 Extreme Events

The COVID-19 pandemic and the Russia-Ukraine conflict in close succession and the disruptions they have caused have brought awareness to the potential vulnerability of food supply chains to extreme events (Bellemare, Bloem, and Lim, 2022). The urgency of investigating food supply chain resilience to such events is heightened by a general recognition that, moving forward, macro forces are likely to make countries increasingly vulnerable to such shocks. For example, the majority of emerging infectious diseases originate in wildlife animals and transmit through interactions among wildlife, domestic animals, and humans within rapidly changing environments and expanding contacts between humans and wildlife, accelerating the potential for pandemic events (Wolfe, Dunavan, and Diamond, 2007; Jones et al., 2013; Allen et al., 2017). A consensus has also emerged that climate change is associated with increasing incidence and intensity of severe weather events, including extreme temperatures, extreme precipitation, and drought (Wuebbles et al., 2014; Cornwall, 2016). Finally, the destructive capacity of geopolitical conflicts is exacerbated by modern conventional weaponry, as well as the risk of introduction of biological weapons onto the battlefield.

Table 1 outlines three categories of extreme events and their potential impacts on stages of the food supply chain. The magnitude of shocks will vary widely depending on specific contexts, and table 1 is meant to be illustrative, not exhaustive. We make no attempt to study the most extreme "extinction" events that could occur, such as nuclear conflict or asteroid or comet impact on the Earth. Such events are predicted to have long-lasting impacts such that coping with them would require massive stockpiling of food reserves, which is not considered in this model.

3 Model

Resilient food supply chains for the US and many other economies means an ability to sustain food production and consumption without undue reliance on international trade because

Event	Farm Supply	Consumer Demand	Processing Capacity
Pandemics	Negative: Shock to labor and other farm inputs	Positive: Stockpiling behavior in short-run Negative: Recession and mortality in long-run	Negative: Health-related plant shutdowns
Natural Disasters & Extreme Weather	Negative: reduced yields and livestock fatality	Positive: Stockpiling	No likely impact unless facilities are destroyed or damaged
Geopolitical Conflict	Negative: Reduced planting and harvesting	Positive: Stockpiling Negative: Recession and mortality in long-run	Negative: Potential destruction of facilities. Blocked transportation networks
Range of Impact	-[5%,15%][a]	+[40%, 75%][b]	-[20%, 40%][c]

Table 1: Shocks to the Food supply chain Under Extreme Events

[a]See Lusk and Chandra (2021) for pandemic impacts on farm labor and Lesk, Rowhani, and Ramankutty (2016) for extreme weather impacts on cereal production. The Russia/Ukraine conflict threatens up to about 15% of the global wheat supply.

[b]See figure 1 for author's calculation of consumption shock to beef during COVID-19. See Beatty, Shimshack, and Volpe (2019) for analysis on stockpiling before extreme weather events.

[c]See Lusk, Tonsor, and Schulz (2020); Martinez, Maples, and Benavidez (2020) for documentation of plant shutdowns due to the COVID-19 pandemic.

catastrophic events are likely to curtail trade due to disruptions in transportation networks and/or country bans imposed on exports and imports (Raj, Brinkley, and Ulimwengu, 2022).[2] We, thus, consider a closed-economy model of a supply chain containing farm production, processing and retailing, and consumption.[3] We assume fixed proportions in production throughout the supply chain in the sense that a given volume of the farm product is required to produce a unit of the consumer good. Given fixed proportions, the output produced at each stage of the supply chain can be equalized given appropriate measurement units and

[2]The Russia-Ukraine conflict provides ample examples of both trade effects. Ukrainian grain and oilseed exports are mainly transported by ocean vessel emanating from the Port of Odessa and were curtailed due to a blockade by Russian forces. Many countries curtailed trade with Russia under sanctions. Meanwhile, other countries imposed export restrictions due to rapidly rising prices for key commodities. Another contemporaneous example of export bans exacerbating food shortages and raising food prices is the escalation of world grain prices in 2007-2008 that led to restrictions or bans on grain exports in Argentina, India, Kazakhstan, Pakistan, Ukraine, Russia, and Vietnam (Mitchell, 2008).

[3]In addition to the fact that catastrophic events are likely to disrupt international trade, a closed-economy specification also makes sense given our focus on the US and calibration to US data. Over 87% of food consumed in the US is produced domestically according to the USDA.

henceforth is denoted by Q.

To simplify exposition of the base model, we assume the food product is produced and processed in a single region ($R = 1$). The model is later extended to incorporate multiple production regions as a resilience-enhancing strategy. The inverse supply function of farmers in the production region is:

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

where X denotes supply shifters, and μ is a parameter to depict a supply shock.

Consistent with past supply-chain models, e.g., Gardner (1975), Wohlgenant (1989), Holloway (1991), Sexton (2000), we assume an integrated processing-retailing sector.[4] n homogeneous processors exist in the region. They may exercise buyer power over farmers and seller power over consumers. Consistent with the norm for most industries, processors may operate multiple plants, so total plants, denoted by N, equals or exceeds the number of processors: $N \geq n$.

Processors collectively face a national demand for the retail product.[5] Consumer demand for the processed product is:

$$P^r(Q) = D(Q|Y, \sigma), \tag{2}$$

where Y contains demand shifters, and σ is a parameter to depict shocks to demand.

Suppressing notation for shifters and shock variables, the objective function for a vertically integrated, profit-maximizing processor j choosing the output q_j is:

$$\max_{q_j} \pi_j \equiv (P^r(Q) - P^f(Q))q_j - c^w q_j, \tag{3}$$

[4]An analytically equivalent approach is to assume a separate, competitive food retailing sector, which operates with constant unit costs.

[5]This formulation is consistent with the idea that, although regional markets may exist for bulky and perishable farm products, final products are less bulky and perishable and easier to transport and, thus, have a broader geographic market than for procurement of the farm product.

where $c^w q_j$ is the total cost of processing for processor j. We assume that all processors have access to the same technologies and, thus, this cost function is common among them. Further, consistent with prior research (Gardner, 1975; Holloway, 1991; Sexton, 2000), we assume constant marginal costs, c^w, but allow c^w to be shifted up or down based on the plant number, N, to allow for possible economies of size, as we explain in the next subsection.[6]

Given that processors are homogeneous, optimization yields symmetric behavior in equilibrium (i.e., $q_j = q_k = q$). Taking the first-order condition and converting derivatives to elasticities, we hence obtain (Sexton and Zhang, 2001):

$$P^r(1 - \frac{\xi}{\eta}) - c^w = P^f(1 + \frac{\theta}{\epsilon}), \tag{4}$$

where $0 \leq \theta \leq 1$ is the processor's buyer power parameter, $0 \leq \xi \leq 1$ is the processor's seller power parameter, $\eta > 0$ is the absolute magnitude of demand elasticity evaluated at the market equilibrium, and $\epsilon > 0$ is the farm supply elasticity evaluated at the market equilibrium. The left-hand side represents the processor's perceived net marginal revenue (PMR) from selling an additional unit of the final product, while the right-hand side is its perceived marginal cost (PMC) of acquiring an additional unit of the farm product.

The model parameterizes both buyer and seller market power on the unit interval, with $\xi, \theta = 0$ denoting perfect competition, $\xi, \theta = 1$ denoting pure monopoly/monopsony, and $\xi, \theta \in (0, 1)$ denoting different degrees of oligopoly/oligopsony power. The model does not presuppose a particular form of market competition, but, rather, seeks to measure the implications of specific departures from perfect competition, which may arise due to unilateral power of the intermediaries, such as under Cournot-Nash competition, or from tacit or overt collusion.

[6]Each processor j that operates multiple plants, $N_j > 1$, must allocate its optimal farm-product purchases and processed product output, q_j^*, across its processing facilities. We do not model this allocation process explicitly, but assume plants are located optimally within the producing region. Hence, each plant operates with the same marginal costs, c^w, produces an equal share, q_j^*/N_j, of the total firm output.

Analytical Solutions

To obtain analytical solutions, we assign linear functions to the model. Suppressing the shock parameters in the functions, we let the farm supply and market demand functions be:

$$P^f(Q) = b + \beta Q, \tag{5}$$

$$P^r(Q) = a - \alpha Q, \tag{6}$$

where a and b capture the effects of the shifter variables for farm supply and consumer demand, respectively.

To capture potential economies of size in processing, we specify the marginal processing cost function as:

$$c^w = c^w(N). \tag{7}$$

Specifically, we allow marginal cost to be locally constant for small changes in firm-level output, but to be a function of the total number, N of processing plants operating in the market. This specification is a convenient way to study processing efficiency because policy proposals involving processor entry or expanding production into multiple regions directly involve increasing N. Equilibrium output of each processing plant changes discretely as a function of N, given the farm supply function. Thus, $\frac{\partial c^w}{\partial N} > 0$ reflects economies of size, and $\frac{\partial c^w}{\partial N} = 0$ represents constant returns to size. Diseconomies of size is not considered due to lack of empirical support for it.

In the risk-free and competitive world, the equilibrium condition is:

$$(a - \alpha Q) - c^w = b + \beta Q, \tag{8}$$

which yields the competitive equilibrium output of the industry:

$$Q^c = \frac{a - b - c^w}{\alpha + \beta}. \tag{9}$$

The equilibrium retail and farm prices are obtained by plugging Q^c into the demand and farm supply functions, respectively.

Similarly, we can find equilibrium output and prices under imperfect competition. The first-order condition becomes:

$$(a - \alpha Q)(1 - \frac{\xi}{\eta}) - c^w = (b + \beta Q)(1 + \frac{\theta}{\epsilon}). \tag{10}$$

We can derive the market's risk-free oligopoly-oligopsony equilibrium output, farm price, and retail price by solving the system consisting of equations 5, 6, and 10:

$$Q^{oo} = \frac{a(1 - \frac{\xi}{\eta}) - b(1 + \frac{\theta}{\epsilon}) - c^w}{\alpha(1 - \frac{\xi}{\eta}) + \beta(1 + \frac{\theta}{\epsilon})}, \tag{11}$$

where $Q^c > Q^{oo}$ for all positive ξ and θ, and Q^{oo} decreases in ξ and θ. The output per processing firm is $q^{oo} = \frac{Q^{oo}}{n}$. The equilibrium retail price is $P^{r,oo} = a - \alpha Q^{oo}$, and the equilibrium farm price is $P^{f,oo} = b + \beta Q^{oo}$.

Given the parameterized model and equilibrium prices and output, the economic surplus measures for consumers, farmers, and processors are straightforward to derive. Consumer surplus (CS) equals $\frac{1}{2}(a - P^{r,oo})Q^{oo}$, producer surplus (PS) equals $\frac{1}{2}(P^{f,oo} - b)Q^{oo}$, and processor profits is $(P^{r,oo} - P^{f,oo} - c^w)Q^{oo}$. The dead-weight-loss (DWL) from market power is given by $\frac{1}{2}(P^{r,oo} - P^{f,oo})(Q^c - Q^{oo}) - c^w(Q^c - Q^{oo})$.

Measure of Resilience

Researchers have used the variance or standard deviation of a variable or welfare measure of interest, like industry-level output or CS, to measure volatility under a given shock (e.g., Ma and Lusk (2021)). However, to compare the volatility of several random variables with different mean values, the coefficient of variation (CV), the standard deviation of a variable divided by its mean, is the most appropriate measure of relative dispersion (Curto and Pinto, 2009).

CV provides a dimensionless measure of *relative* volatility that is widely used in economic risk assessments, like financial stability (Pinches and Kinney, 1971; Ozkok, 2015), socioeconomic inequality (Houthakker, 1959; Braun, 1988), and agronomic yield variability (Kravchenko et al., 2005). In the context of supply chain resilience, CV measures the relative dispersion of CS, PS, and intermediary profits under a set of extreme shocks to the system. It allows US to compare the volatility of welfare for supply-chain participants (producers, intermediaries, consumers), who have different average surplus measures, across different policy proposals and supply-chain structures.

Parameterization

To parameterize the model, we normalize the risk-free, competitive equilibrium industry-level output to 1.0. The corresponding equilibrium retail price on the national market is $a - \alpha Q^c$ and also normalized to 1.0. The corresponding demand elasticity at this equilibrium, η, hence equals $\frac{1}{\alpha}$, and $a = 1 + \alpha = 1 + \frac{1}{\eta}$.

On the supply side, the competitive farm equilibrium price is $f = 1 - c^w$, where c^w is a function of the number of processors, N, and, hence, the economies of size a given processor is able to obtain. This farm price is the farm share of the normalized retail value of a unit of the product under perfect competition. Total farm output is also 1.0. Thus, $\beta = \frac{f}{\epsilon}$ and $b = f(1 - \frac{1}{\epsilon})$, where ϵ is the farm price elasticity of supply at the competitive equilibrium.

As noted, allowing for the presence of economies of size in processing is critical in our model. Economies of size in food processing have been studied most extensively for the meatpacking industries, wherein size economies have generally been found to exist and to be substantial. Morrison Paul (2001) shows that the cost function for US beef processing can be expressed approximately as $C(q) = mq^g$ where m is a multiplier, q is the output of a processor, and $g = \frac{\partial ln(C)}{\partial ln(q)}$ is the cost elasticity of output with $0 < g < 1$ denoting the presence of size economies. Morrison Paul (2001) reports estimates of $g \approx 0.95$ for US beef processing. MacDonald and Ollinger (2000) report a nearly identical cost elasticity estimate for US hog processing. Ollinger, MacDonald, and Madison (2005) found even greater scale economies for US poultry, with the cost elasticity estimates for chicken ranging from 0.88 to 0.93. Somewhat greater scale economies were found for turkey processing.

To adapt these size economy estimates to our model structure, we express marginal processing costs as $c^w(N) = cN^\gamma$, where $\gamma \geq 0$, and equate this expression to marginal cost in Morrison Paul's (2001) model to solve for γ. Here $\gamma = 0$ denotes constant returns to size, while $\gamma > 0$ indicates the presence of economies of size. Given that the equilibrium output per homogeneous plant under perfect competition is $q_j^c = \frac{1}{N}$, we have:

$$mg(\frac{1}{N})^{g-1} = cN^\gamma. \tag{12}$$

Assuming $c = mg$, the equation for γ simplifies to:

$$\gamma = 1 - g. \tag{13}$$

Equilibrium solutions to the model then depend on six parameters (η, ϵ, f, g or γ, ξ, and θ) that are all pure numbers and describe the market structure and three exogenous shock variables to the supply chain. We assigned base values for these parameters by drawing the empirical literature for US meat supply chains. These base values and sources are displayed in table 2.

Parameter	Description	Value	Source
$\|\eta\|$	|Demand elasticity|	0.7	(Okrent and Alston, 2011)
ϵ	Supply elasticity	1	(Chavas and Cox, 1995)
f	Farm share	0.3	(USDA-ERS)
g	Output elasticity of cost	0.95	(Morrison Paul, 2001; MacDonald and Ollinger, 2000)
γ	Economies of scale parameter	$1 - g$	Authors' calculation
ξ,θ	market power parameters	0, 0.15, 0.3	(Sexton and Xia, 2018)
N	Total number of processing plants	40	Garrido et al. (2021)

Table 2: Baseline Parameter Values for Simulation

Correlated Shocks

Destructive events such as a natural disaster, war, or a pandemic that impact labor supplies may negatively impact both farm supplies and available processing capacity (Wahdat and Lusk, 2022). These events also simultaneously and positively shock demand due to consumers attempting to stockpile goods. However, to date the literature on food supply chain resilience has not incorporated the correlated nature of shocks due to extreme events (Davis, Downs, and Gephart, 2021).

To illustrate how extreme events introduce correlated shocks between retail and processing stages, figure 1 displays weekly percentage changes from average in beef slaughter and retail sales in 2020 following onset of the COVID-19 pandemic in the US. The shaded area reflects the initial weeks of the COVID-19 pandemic, mid-March through the end of June. The initial weeks of the pandemic induced panic buying and hoarding of available supplies up to 45% beyond normal retail sales. At the same time, slaughter dropped as much as 32% below average because processing plants were forced to stop operations due to employee illnesses or local ordinances.

Multi-variate joint distributions (or copula) allow for random variables drawn from differing distributions with dependant structures. Copulas are commonly used in quantitative finance for portfolio risk-management, where the volatility of individual investments that compose a portfolio are correlated with each other (Fan and Patton, 2014). For supply chain analysis of extreme events, copulas allow for random draws from a positive half-normal parallel demand shock (σ), negative half-normal parallel supply shock (μ), and binomial processor shutdown shock (N').

Table 1 informs the parameterization of these distributions according to the possible magnitudes of extreme events in percentage terms. The mean and variance of a half-normal distributions are specified by a single scale parameter or θ_H in the set of expressions below. Here, the half-normal parameters correspond to a mean 20% shift in demand (i.e., mean of $\sigma = 0.5$ is 20% of a) and a 30% shift in farm supply (i.e., mean of $\mu = 0.1$ is a third of f).

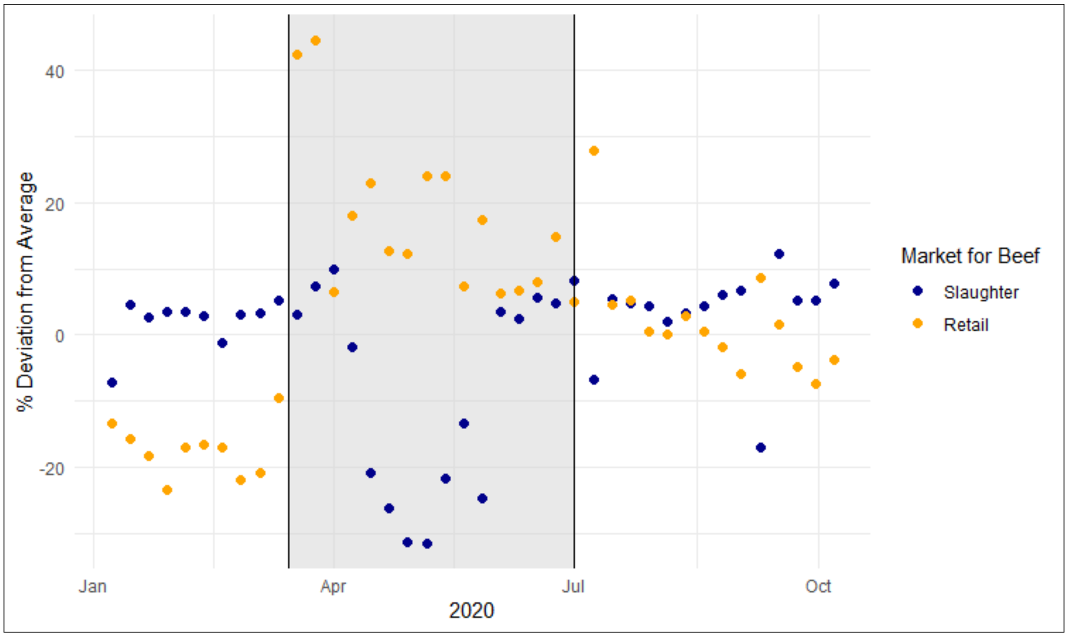


Figure 1: Weekly Beef Slaughter and Retail Sales Relative to Average.
Note: Authors' calculation. Data on retail beef sales are from USDA-ERS Weekly Retail Food Sales. Slaughter data are from Livestock Marketing Information Center (https://lmic.info). The shaded region shows the large deviations from he average in the weeks immediately after the first COVID-19 cases in the US in March 2020.

After parallel shifts, demand and supply curves have new intercepts $a' = a + \sigma$ and $b' = b + \mu$, respectively. The binomial shutdown shock determines the number of processing plants that remain active, N', from a total number of plants, N. On average, 75% of the plants remain in operation after an extreme event in our simulation model.

$$\begin{aligned} \sigma &\sim H(\theta_H = 2) \\ \mu &\sim H(\theta_H = 10) \\ N' &\sim B(N, 0.75) \end{aligned} \tag{14}$$

The magnitude of shocks will vary across different extreme events, but the values chosen here are emblematic of recent experiential evidence. The densities of each shock for our baseline simulations are presented in figure 2.

Given distributions of shocks, we then draw 100,000 sets of shocks from a multi-variate joint distribution, in essence creating 100,000 different extreme events. The dependant nature

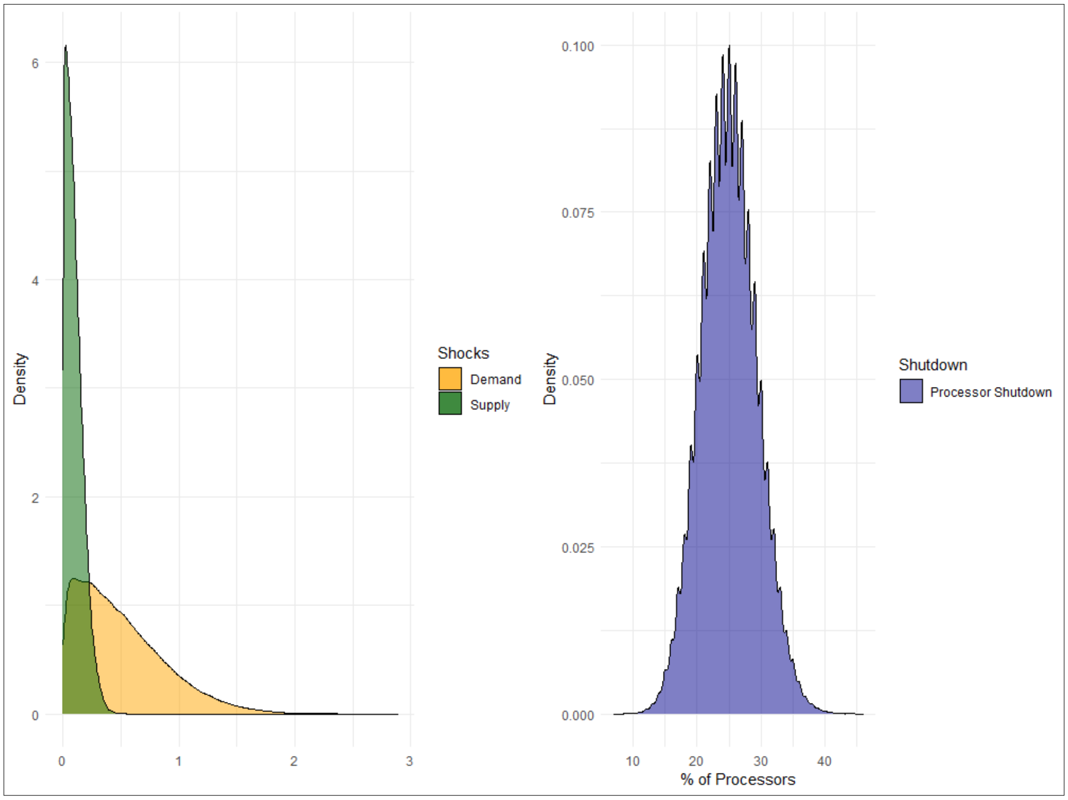


Figure 2: Density of shocks from multi-variate joint distribution.

Note: Left panel displays the density of 100,000 draws from half-normal distributions for the supply and demand shocks. Right panel displays the density across 100,000 draws from a binomial distribution, where 25% of plants shut down on average.

of these shocks are defined by a 3 by 3 covariance matrix, where the off-diagonal elements specify by the degree of correlation, ρ, between each stage's shock. To illustrate the role of correlation between shocks, we simulate over the off-diagonal elements of the covariance matrix for $\rho \in [0, 0.5]$.

Figure 3 displays simulation outcomes for a supply chain with moderate market power ($\xi = \theta = 0.15$) for alternate values of ρ. For this illustrative simulation, all off-diagonal elements are simply equal to ρ, but these elements are fixed at differing baseline values for the policy simulations. The vertical axis measures the percentage change in CV relative to CV under fully independent shocks. Increasing the correlation among shocks increases CV of all welfare measures. Intuitively, a stronger correlation between a and b increases the variance of CS and PS, but has little effect on their means.[7] In the baseline, we allow $\text{cor}(\sigma, \mu) = 0.25$, $\text{cor}(\sigma, N') = -0.5$, and $\text{cor}(\mu, N') = 0.1$.[8]

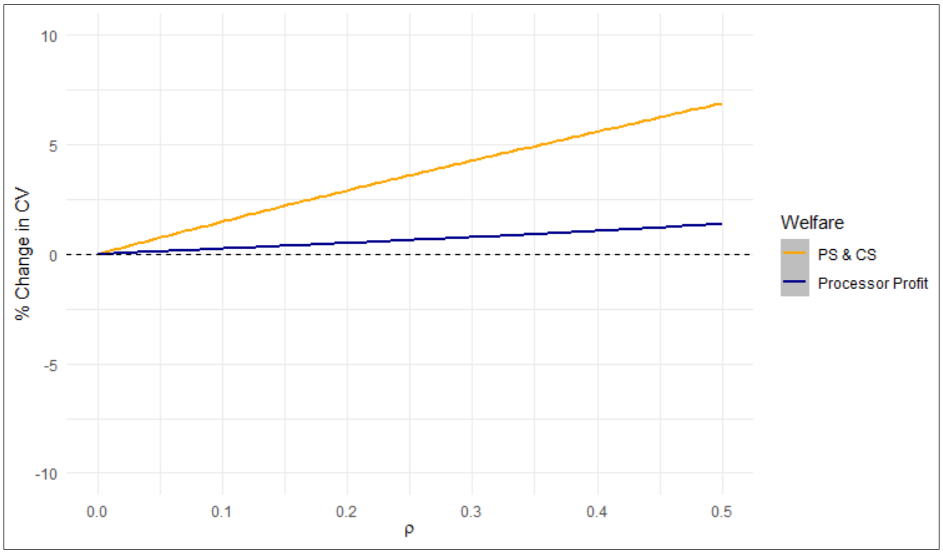


Figure 3: Correlation between shocks at different supply chain stages.
Note: Authors' creation from numerical simulation. Displays the implications of increasingly correlated shocks at different supply chain stages. The vertical axis measures % changes of the CV of producer, consumer, and processor surplus from independently shocks.

Post-Shock Equilibrium

When processing plants experience a shutdown shock (i.e., N falls to N'), we assume that the market power parameters stay unchanged in the short-run, i.e., market power is related to n, not N. At the same time, consumer demand and farm supply curves shift. We assume that operational plants can adjust farm-product acquisitions and processed product outputs to respond to the new consumer demand $(a' - \alpha Q)$ and farm supply $(b' + \beta \frac{N}{N'} Q = b' + \beta' Q)$ functions after shocks occur.[9]

[7]The mean values of CS and PS increase slightly in ρ because the positive demand shift tends to dominate the correlated negative shift in farm supply.

[8]These values are informed by weekly data from the beef supply chain from 2019-2020 and reflect that shutdowns and stockpiling are likely to be highly correlated, supply shifts and demand shifts moderately correlated, and supply shifts and processor shutdowns slightly correlated. Our results are not sensitive to our choices of these correlation values.

[9]For example, additional farm supplies can be called forth by bringing product from storage or accelerating harvesting. Processing throughput can be expanded by operating a Saturday shift, as occurred in beef processing during the COVID-19 pandemic.

Given the new demand and supply function intercepts and supply function slope, the new industry output is:

$$Q^{oo\prime} = \frac{a'(1 - \frac{\xi}{\eta}) - b'(1 + \frac{\theta}{\epsilon}) - c^w}{\alpha(1 - \frac{\xi}{\eta}) + \beta'(1 + \frac{\theta}{\epsilon})}. \tag{15}$$

Per plant output is simply $\frac{Q^{oo\prime}}{N'}$. Equilibrium prices and welfare measures are computed accordingly.

4 Simulations

We study four widely discussed policy responses intended to protect consumers and farmers by reducing supply chain volatility in response to market shocks: 1) reducing intermediary market power, 2) subsidizing the entry of additional processors, 3) limiting consumer price increases through anti-price-gouging laws, and 4) creating regional diversification of production capacity.

We simulate each policy proposal and report its impact on mean economic surplus and the relative volatility, CV, of surplus for farmers, consumers, and market intermediaries. We present the results for the latter three policy interventions for three alternative levels of processor market power: perfect competition ($\xi = \theta = 0$), moderate market power ($\xi = \theta = 0.15$), and high market power ($\xi = \theta = 0.3$) to reflect different market structures in key agricultural industries.[10]

Our simulation outcomes are summarized in the following figures. In each figure, the vertical axis tracks percent changes in the mean welfare measures and their CV as market parameters (e.g., market power parameters ξ and θ) change. The percentage changes along

[10] Although our market power parameters are not tied to a particular form of competition, it is useful to relate them to non-cooperative Cournot competition, where ($\xi = \theta = 0.15$) corresponds approximately to the market power generated by 6–7 symmetric Cournot competitors and to a Hirschman–Herfindahl (HHI) index of approximately 1,500, a value that the US Department of Justice regards as moderately concentrated in its Merger Guidelines. $\xi = \theta = 0.3$ corresponds to Cournot competition involving 3 or 4 symmetric firms, and an HHI index in the range of 2,500 to 3,300, either of which would be considered as highly concentrated by the DOJ under the Merger Guidelines. Notably four-firm oligopoly-oligopsony corresponds roughly to the market structure for the US beef and pork industries (U.S. Department of Agriculture, 2022).

the vertical axis are computed relative to the baseline scenario that is depicted as the leftmost parameter value for each simulation. Appendix C explains mathematically why the mean surplus and CV curves follow particular patterns and why the curves for CS and PS tend to follow the same pattern or overlap. Though the mathematics determining the patterns may be somewhat complicated, numerical simulations and outcomes depict the market resilience and efficiency impacts as we explain below.

Reducing Intermediary Market Power

The economic welfare implications of market power in the food and agriculture sector have long been a focus for agricultural economists (Sexton and Xia, 2018). However, little is known about the resiliency impacts of intermediary market power. Figure 4 shows the impacts of market power in the range $\xi = \theta \in [0, 0.3]$ on resilience measured in terms of CV (left panel) and mean economic surplus (right panel) based on 100,000 simulations for each value of $\xi = \theta$.

The right panel displays the well-understood result that, as intermediary market power decreases, consumers and producers gain economic surplus and processors lose profits. Less understood, however, is that CV for consumers' and farmers' surplus also decreases as the intermediary market power falls, as does CV of processors' profits. Both the standard deviation of surplus and its mean value for farmers and consumers rise as the level of processor market power drops, but mean surplus rises faster than the standard deviation, causing CV to fall.[11]

These results are the first demonstration that, in the presence of correlated economic shocks, consumers and farmers benefit from both higher average economic surplus and reduced variability of surplus from policies that induce more competitive supply chains. Thus,

[11] Intermediaries with market power rationally pass on less of a demand or supply shock to farmers and consumers than would occur in a perfectly competitive market because they internalize a portion of the impact their output decision has on the farm price and consumer price. Conversely, perfect competitors treat these prices as given. Appendix C provides a mathematical explanation for why CV for CS and PS falls as intermediary market power drops under positive demand shocks and negative farm supply shocks.

policies designed to increase competition among market intermediaries may represent “win-win” outcomes for consumers and farmers.

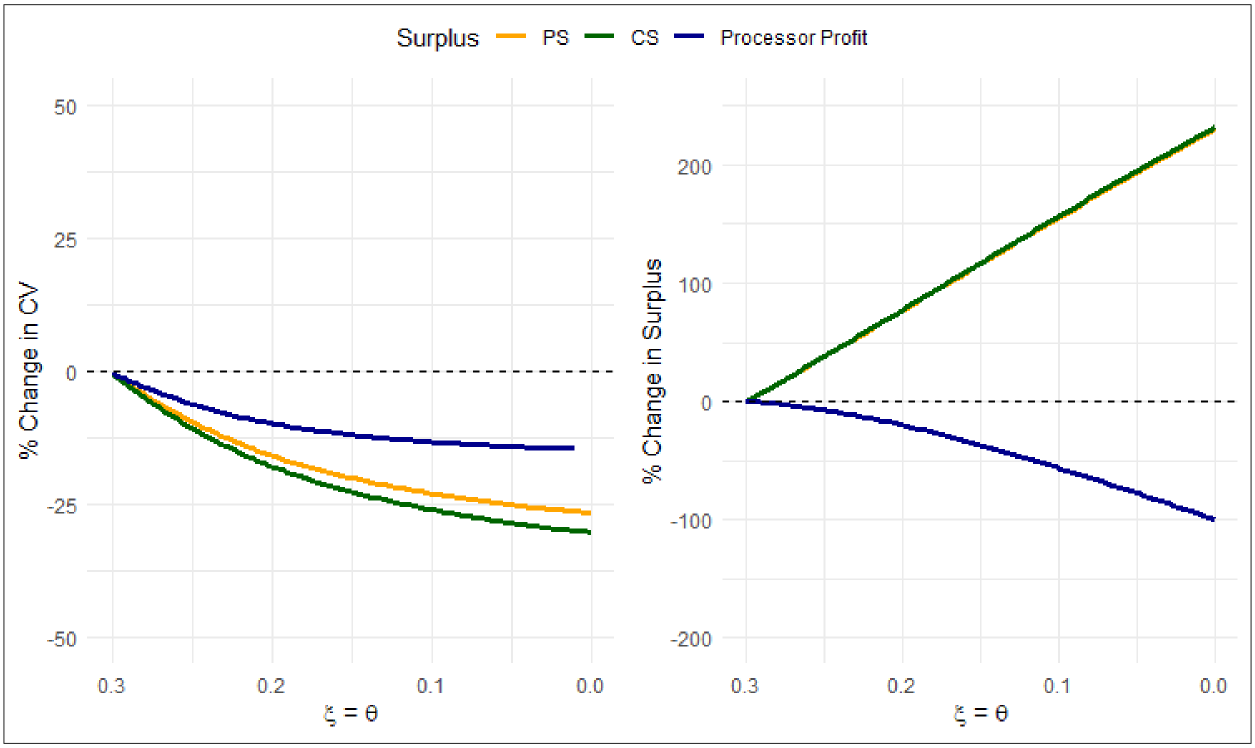


Figure 4: Impacts of decreasing intermediary market power on resilience and welfare.

Note: Authors' creation from numerical simulations. The vertical axis measure the % changes relative to high market power ($\xi = \theta = 0.3$). Left panel displays the reliance gains from more competitive markets. Right panel shows that producer and consumer surplus increase, and processor profit declines as market power decreases.

Entry of Processors

One of the primary policy responses in the US to the COVID-19 pandemic and disruptions caused in the meat supply chains is a USDA initiative which provides $500 million to support entry of new firms into meat and poultry processing (U.S. Department of Agriculture, 2021).[12] The objectives of this policy are to increase competition in local regions and to reduce bottlenecks in meat processing under shutdown risk.

[12]While meat processing has received the most intense scrutiny due to allegations of anti-competitive behavior, other segments of food supply chains have received similar critiques. In early 2022, for example, USDA launched an investigation into the fertilizer, seed, and food retail markets as a result of heightened prices (U.S. Department of Agriculture, 2022).

The potential resiliency improvements from entry into processing are twofold. First, additional processing plants disperse shutdown risks over a larger number of operations, thus diversifying the risk of losing processing capacity and reducing variance in industry output. Second, additional processors potentially increase competition among processors, which, as figure 4 demonstrates, increases average surpluses to farmers and consumers and decreases the CV of those surpluses.

The main focus of the US policy is to support entry of small-scale processors. Given our model, we simulate entry by processors that are symmetric with the incumbent processors. This approach errs in favor of a policy to stimulate entry because entrants have the same marginal cost as incumbent processors and expand market competition in ways that small-scale entrants may be unable to accomplish.[13] Counterbalancing the enhanced resiliency and reduced market power from adding processors is that per plant throughput declines as more plants are added for a given farm supply function, meaning that firms are less able to exploit the available economies of size.

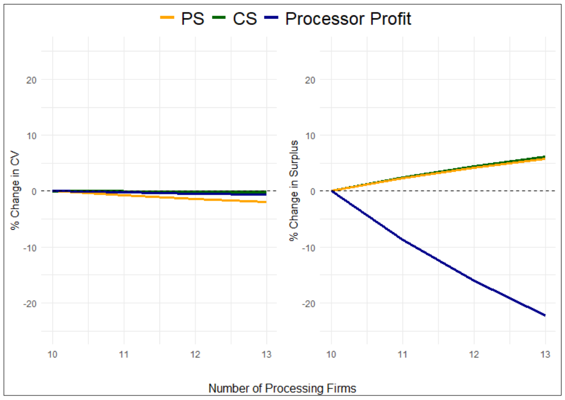
We simulate adding processors for each of the three market competition scenarios and assume that market power parameters are dependent on n, reflecting symmetric, non-cooperative Cournot competition among processors, such that $\xi = \theta = \frac{1}{n}$. Each processor operates $\frac{N}{n}$ plants, where N is equal to 40 in the baseline in accordance with table 2. Therefore, as n increases, the total number of processing plants simultaneously increases, dispersing the risk of plant shutdown. The nearly competitive scenario begins with $n = 10$ processors and sequentially introduces entering processors to reach $n = 13$. Processor market power is less consequential in these setting ranging from $\xi = \theta = 0.08$ for $n = 13$ to $\xi = \theta = 0.10$ for $n = 10$. Similarly, moderate market power is reflected by $n = 6$ ($\xi = \theta = 0.17$) to $n = 9$ ($\xi = \theta = 0.11$) and high market power by $n = 3$ ($\xi = \theta = 0.33$) to $n = 5$ ($\xi = \theta = 0.20$). We also show the simulation results holding market power constant in each simulation in

[13]For example, small food processors may only serve local or regional markets, leaving national concentration largely unaffected.Appendix A depicts simulations for the case where processor entry does not affect processor market power.

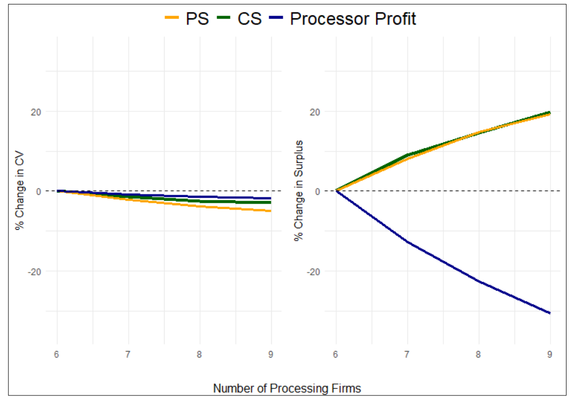
Appendix A and figure A1, thereby isolating the impacts of entry on plant shutdown risk and plant economies of scale.

For each value of n, we simulate 100,000 correlated shocks to demand, supply, and processing capacity. The simulation results from increasing the number of food processors are presented in figure 5, with panels (a), (b), and (c) depicting the results for near perfect competition, moderate market power, and high market power, respectively.

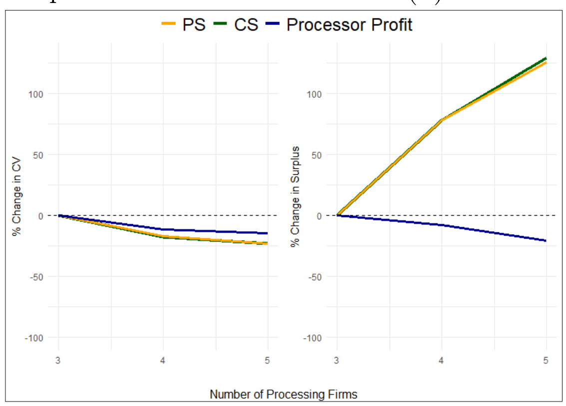
Similar to figure 4, these simulations show that lower levels of market power (larger n) are associated with smaller volatility relative to average welfare for producers and consumers. Additionally, mean CS and mean PS overlap and rise as market power diminishes. The resilience and efficiency improvements are greater for small values of n. That is, there are decreasing returns from adding n. Thus, stimulating entry is most effective in enhancing resilience, when it is done in markets with low n or high market power *ex ante*. Figure A1 further shows that these resilience and efficiency improvements are mostly attributed to the reduced market power effect. When market power is held constant, the economies of scale penalty from reduced throughput per plant unequivocally reduces average welfare outcomes for all agents. Thus, the efficacy of policies to induce processing plant entry hinge importantly on whether such entry reduces processor market power.



(a) Nearly Competitive



(b) Moderate Market Power



(c) High Market Power

Figure 5: Impacts of processor entry on average market surplus and CV of surplus
Note: Authors' creation from numerical simulations. Vertical axis measure the % changes in CV (left panel) and mean surplus (right panel) relative to the baseline number of processors for each scenario.

Anti-Price-Gouging Laws

About two-thirds of US states have price-gouging laws that engage during natural disasters or declared emergencies and that limit increases in retail prices during such episodes (Morton, 2022). These laws were triggered in a number of jurisdictions in response to the COVID-19 pandemic. Price caps may also be imposed on an *ad hoc* basis under emergency powers that political leaders often have.

A key unanswered question, however, is how such anti-price-gouging laws impact supply chain resilience. When price is not allowed to signal market conditions and equilibrate the available supply with demand, shortages may ensue, and available products may not be allocated to the highest-valued consumer. Counterbalancing this effect is the fact that price ceilings do eliminate sellers' ability to exercise market power over a range of prices and, thus, may lead to increased industry output and higher CS and PS.

To illustrate the impact of anti-price-gouging laws, consider the case where retail prices are fixed at the risk-free (pre-shock) level: $P^{r,oo} = a - \alpha Q^{oo}$ as specified in equation (2).[14] Allowing for flexible prices, the new equilibrium quantity produced post-shock, $Q^{oo'}$, is given by equation (15) and yields the flexible retail price $P^r(Q^{oo'}) = P^{r,oo}_{flex}$. The impact of capping the retail price at the pre-shock level, $P^{r,oo} = P^{r,oo}_{fix}$, is illustrated by two cases described in figure 6.

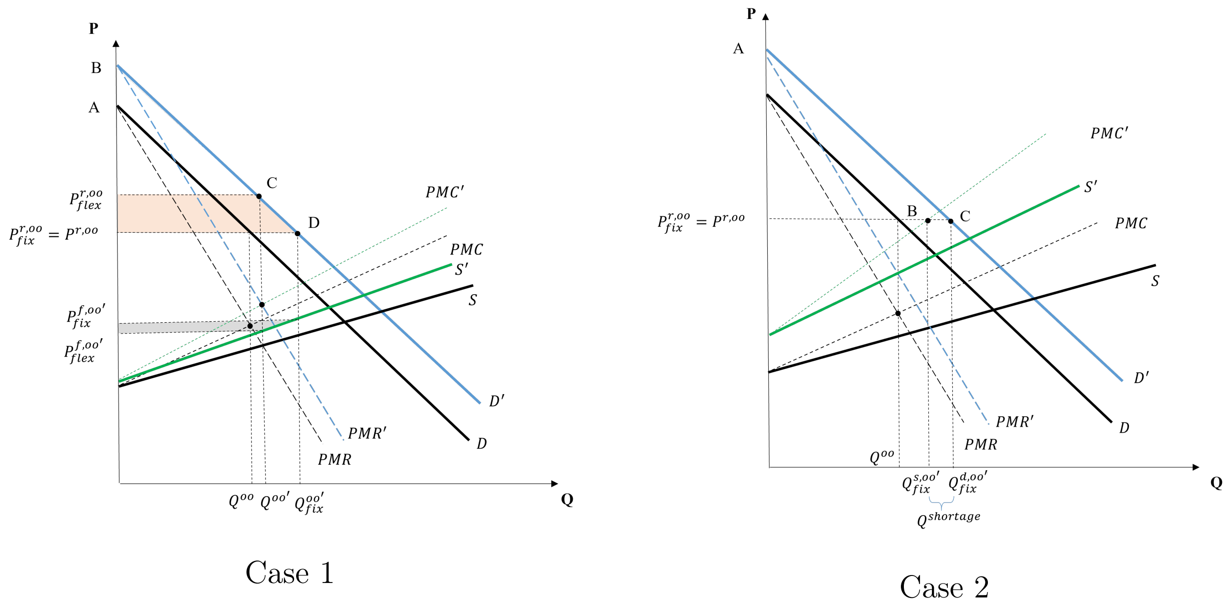


Figure 6: Fixing the post-shock retail price at the pre-shock level

Note: Authors' creation. Case 1 illustrates a market setting wherein a price-ceiling eliminates seller power and does not cause a market shortage. Case 2 illustrates a post-shock equilibrium where the price ceiling does create a market shortage, with quantity demanded exceeding quantity supplied at the fixed price.

In Case 1 (left panel), the price ceiling, $P^{r,oo}_{fix}$, intersects the new demand curve, D', at $Q^{oo'}_{fix}$, before it intersects the post-shock PMC curve, PMC'. For all $Q \leq Q^{oo'}_{fix}$, $PMR(Q) = P^{r,oo}_{fix} > PMC'$. For any output larger than $Q^{oo'}_{fix}$, $PMR(Q) < PMC'$. Therefore, the

[14] Anti-price-gouging laws may also be applied to farm prices. Appendix B studies the case of price fixed at the farm level.

processors produce $Q^{oo'}_{fix} > Q^{oo'}$ and charge the ceiling price, $P^{r,oo}_{fix}$. No shortage is created by the price ceiling. Both CS and PS increase relative to the flexible-price case, with the gain to consumers (producers) indicated by the pink (gray) shaded areas.

In Case 2, $P^{r,oo}_{fix}$ intersects (PMC'), at point B, before it intersects D'. Processors maximize profits by producing quantity $Q^{s,oo'}_{fix}$, while consumers demand $Q^{d,oo'}_{fix}$, resulting in a market shortage equal to $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$.[15]

Given a shortage, the market could clear in various ways. For example, product could be allocated based on queues, and secondary markets could possibly reallocate product from low- to high-demand consumers. However, secondary resale markets for foods subject to shortage did not occur with any frequency in the US during the COVID pandemic, nor were consumer queues common. Rather, available products were allocated seemingly at random based on when shelves were restocked and consumers happened to arrive at stores.

We, thus, assume that the quantity supplied, $Q^{s,oo'}_{fix}$, is randomly allocated among all consumers who are willing to purchase at $P^{r,oo}_{fix}$. Consumer surplus is then computed by:

$$\frac{Q^{s,oo'}_{fix}}{Q^{d,oo'}_{fix}} \int_0^{Q^{d,oo'}_{fix}} \left(D'(Q) - P^{r,oo}\right) dQ. \tag{16}$$

Failure of product to be allocated to the consumers who value it most represents a welfare loss from fixed prices that offsets the benefit of fixed prices in reducing processor oligopoly power.

Anti-price-gouging laws typically allow some flexibility in prices post-shock.[16] We, hence, incorporate a continuum of price flexibility in the simulations from the pre-shock level, $P^{r,oo}$ by setting price $\bar{P}^{r,oo} = P^{r,oo}(1+\omega)$ for $\omega \geq 0$. Smaller values of ω denote a tighter price ceiling. For sufficiently large values of ω, the price ceiling will not bind. We

[15]Both cases depicted in figure 6 show post-shock output increasing relative to the pre-shock equilibrium. Output may decrease depending on the magnitude of shocks and extent of processor market power. Appendix B discusses this case.

[16]California's Penal Code Section 396, for example, prohibits price increases by more than 10% after an emergency declaration or 50% above the seller's cost to produce the good or service.

present simulation results in figure 7 for $\omega \in [0, 0.60]$, where $\omega = 0.60$ allows sufficient price flexibility that the ceiling does not bind in our model, while $\omega = 0$ represents no flexibility and price is fixed at the pre-shock level.

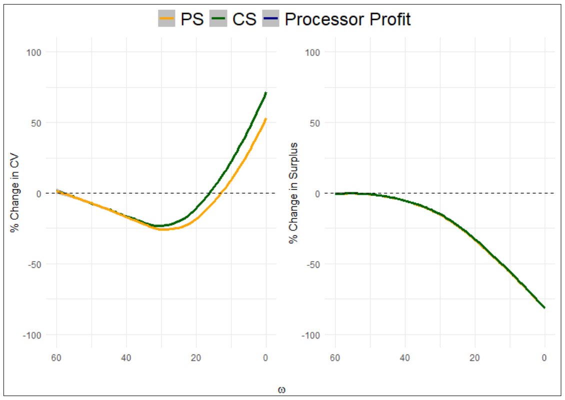
The three panels reflect both of the two possible cases of price ceilings illustrated in figure 6. Panel (a) depicts a perfectly competitive market, so $\bar{P}^{r,oo}$ represents Case 2 across all values of ω. Mean CS and PS is increasing in ω, while processor profits are zero for all ω under perfect competition.[17] Larger values of ω are associated with reduced volatility of welfare. More stringent price ceilings (i.e., $\omega < 15\%$) however, increase CV for both consumers and producers, reducing resilience. CS and PS also fall due to the induced shortages they create, resulting in a "lose-lose" scenario.

Panel (b) illustrates a supply chain with moderate market power. Here, Case 1 emerges and yields higher values for CS and PS for all but the most stringent price ceilings. These benefits are maximized when $\omega \approx 15\%$. As the price ceiling becomes stricter, a mix of Cases 1 and 2 holds across the 100,000 simulations. CV of CS and PS also have a nonlinear relationships with ω. The resilience improvement is maximized at $\omega = 0$ with the CV reduced by 30% from the flexible-price level. For $\omega > 20\%$, the relative volatility for CS and PS is higher than the flexible-price level. A "win-win' outcome can be achieved for ω ranging from about 0.05 to 0.15.

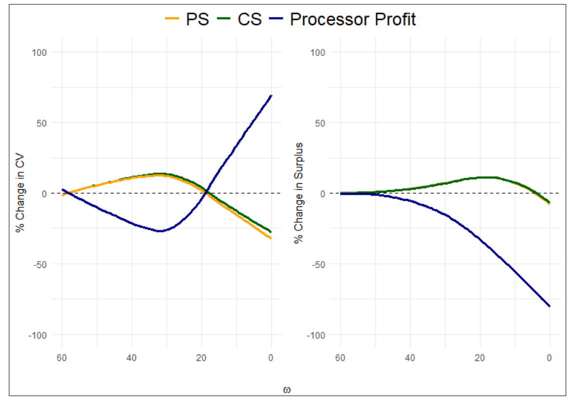
Panel (c) depicts a higher level of processor market power and the predominance of Case 1. Price ceilings increase consumer and producer welfare the most in these settings because of their market-power-reducing effect. The increase in CS and PS is greatest for the most stringent price ceilings. However, the CV of CS and PS is larger over most of the range of ω. For example, at $\omega = 20\%$, CV of CS and PS is greater by upwards of 40% compared to the market with no price restriction. Thus, under higher intermediary market power, anti-price-gouging laws benefit producers and consumers most by transferring surplus to them

[17] Under perfect competition, a binding price ceiling leads to welfare losses for both producers and consumers due to the shortage that necessarily occurs in the competitive case and restricting both farm production and consumption below the surplus-maximizing levels. See more discussion in Appendix B. For example, allowing prices to increase by no more than 10% lowers average CS and PS by about 35%.

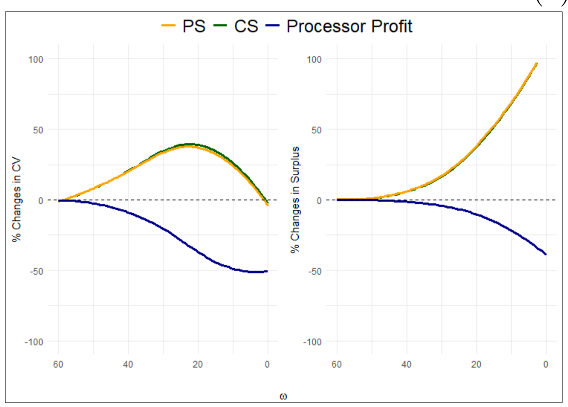
from intermediaries, but they do not improve the resilience of supply chains. A win-win outcome for producers and consumers can, however, be achieved as ω approaches zero.



(a) $\xi = \theta = 0$



(b) $\xi = \theta = 0.15$



(c) $\xi = \theta = 0.3$

Figure 7: Impacts of anti-price-gouging laws on market surplus and resilience.
Note: Authors' creation from numerical simulations. Vertical axis measure the % changes relative to a fully flexible prices. The impacts of price ceilings are highly non-linear and depend critically on market structure. Processor profit is omitted from panel (a) because it is zero in all cases.

Figure 8 illustrates the effects of binding price ceilings on market shortages under the different market competition scenarios. The vertical axis measures shortage as the difference between the normalized quantity demanded and the quantity supplied at the fixed price. Despite the fact that price is more stable and seller power is essentially eliminated with a strict anti-price-gouging law, such a law does not necessarily improve farmer and consumer welfare or reduce the volatility of CS and PS for creating shortage of supply. Anti-price-gouging laws are most likely to increase CS and PS the less competitive is the market, but in these cases, as figure 7 demonstrates, the laws often increase the volatility of producer and consumer returns as measured by CV.

Although we have simulated an anti-price-gouging law for a single supply chain, in reality they paint with a “broad brush.” They generally apply to all food and drink products, as well as a variety of other products deemed as necessities. Thus, these laws will apply to food markets regardless of their competitive structure. The efficacy of these laws thus depends importantly on overall competitive conditions of food markets within the implementing jurisdiction and the stringency with which price increases are restricted.

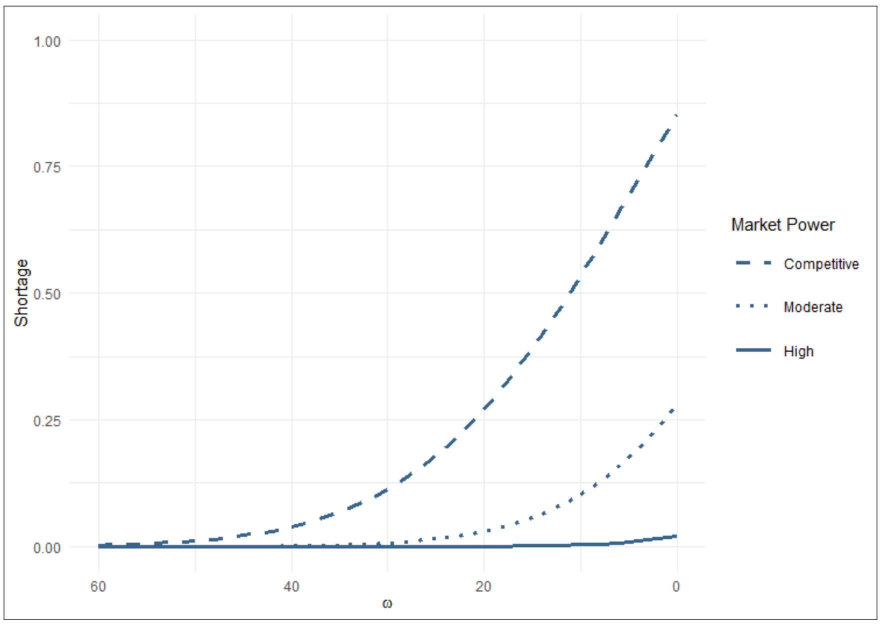


Figure 8: Market shortage with a price ceiling with different levels of market power.

Note: Authors’ creation from numerical simulations. The vertical axis measures the difference between normalized quantity demanded and quantity supplied under the level of price ceiling. The curves show that a price ceiling introduced in a competitive market induces a greater shortage compared to the same ceiling implemented in an imperfectly competitive market.

Regional Diversity of Farm Production

Agricultural production in the US has become increasingly geographically concentrated as regions produce according to their comparative advantage. For example, California has become the dominant US producer of many fruits, vegetables, and tree nuts. Distributing agricultural production and processing across geographically diverse regions and emphasizing localized food systems has been proposed as a resilience strategy (Raj, Brinkley, and Ulimwengu, 2022) because supply shocks in one region may not impact other regions, geographically diversified food systems may be able to adapt more nimbly to extreme shocks than concentrated systems (Thilmany et al., 2021; U.S. Department of Agriculture, 2022).

Although diversifying production of key commodities across multiple regions may enhance the supply chain's resilience to some shocks, it will likely come at a cost of reduced production efficiency (Sexton, 2009). To explicate this trade-off in the simplest way, we examine the marginal change of expanding from a single production and processing region to two. To ensure analytical solutions, we assume that each region has the same number of plants, and the plants belong to the same group of symmetric processors. It follows that the two regions have the same buyer power and seller power. Processing costs are thus $c^w = c \times (RN)^\gamma$, where $R > 1$ denotes the number of production regions.

The retail market is national as in the baseline case, and we assume that no farm product is transferred between production regions, thereby allowing plants in different regions to face different supply functions:

$$\begin{aligned} P_1^f(Q_1|X_1, \mu_1) &= b_1 + 2\beta Q_1 \\ P_2^f(Q_2|X_2, \mu_2) &= b_2 + 2\beta Q_2, \end{aligned} \tag{17}$$

where subscript 1 refers to the base region of farm production and 2 refers to the new region.[18]

Solving the two-region system, we obtain the equilibrium total output:

$$\tilde{Q^{oo}} = \frac{a(1 - \frac{\xi}{\eta}) - \bar{b}(1 + \frac{\theta}{\epsilon}) - c^w}{\alpha(1 - \frac{\xi}{\eta}) + \beta(1 + \frac{\theta}{\epsilon})}, \tag{18}$$

where $\bar{b} = \frac{b_1 + b_2}{2}$. Plugging $\tilde{Q^{oo}}$ into the first-order-conditions, we obtain the pre-shock

[18]When $b_1 = b_2 = b$ (here b is the supply function's intercept in the baseline setup) and if c^w is the same as in the baseline, each region produces exactly one half of the equilibrium output in the one-region scenario, Q^c, and regions have the same supply elasticity under perfect competition.

regional equilibrium output:

$$\tilde{Q_i^{oo}} = \frac{a(1-\frac{\xi}{\eta}) - \bar{b}(1+\frac{\theta}{\epsilon}) - c^w + \frac{\alpha(1-\frac{\xi}{\eta})}{\beta}(\bar{b}-b_i)}{2\alpha(1-\frac{\xi}{\eta}) + 2\beta(1+\frac{\theta}{\epsilon})}, \tag{19}$$

where $i = 1, 2$. The term, $\frac{\alpha(1-\frac{\xi}{\eta})}{\beta}(\bar{b}-b_i)$, in the numerator is the deviation from half of the industry output or $\frac{Q_i^{oo}}{2}$. Intuitively, the larger b_i or the more costly it is to produce farm outputs in region i, the less the region produces in equilibrium. If $b_2 > b_1$, the new region produces less than the incumbent region due to higher production costs.

The two regions face independent supply shocks (μ_1, μ_2) and the same demand shock at the national level in the simulations. The supply function of region 2 has an intercept equal to $b + k$ where $k = f \times 0.23 = 0.069$, reflecting production costs that are 23% higher than the first region due to the cost inefficiencies of local production found by Sexton (2009). Each region also faces independent shutdown risks among its plants, so that N_i' plants remain active in region i. As a result, PS differs across regions and equals $\frac{P_i^f \tilde{Q_i^{oo}}}{2} = \beta_i' \tilde{Q_i^{oo}}^2$. When $b_2 > b_1$, $PS_2 < PS_1$.

The post-shock equilibrium output equals:

$$\tilde{Q^{oo'}} = \frac{a'(\beta_1' + \beta_2')(1-\frac{\xi}{\eta}) - B(1+\frac{\theta}{\epsilon}) - (\beta_1' + \beta_2')c^w}{\alpha(\beta_1' + \beta_2')(1-\frac{\xi}{\eta}) + 2\beta_1'\beta_2'(1+\frac{\theta}{\epsilon})}, \tag{20}$$

where $\beta_i' = \beta \frac{N}{N_i'}$ and $B = b_1'\beta_2' + b_2'\beta_1'$. Region i's output is found from the first-order-condition of the region given $Q^{oo'}$:

$$(a' - \alpha Q^{oo'})(1 - \frac{\xi}{\eta}) - c^w = (b_{i'} + 2\beta_i' Q_i^{oo'})(1 + \frac{\theta}{\epsilon}). \tag{21}$$

The simulation results are presented in figure 9. Surpluses decline in all panels and for all agents. There are resilience benefits for farmers from diversifying production regions, but consumers' CV rises. When market power is high, for example, the decrease in mean

CS is as much as 15% and that of PS is close to 10%, while the decrease in CV for PS is about 10% and CV for CS rises by 5%. Consumers suffer from higher relative volatility because mean CS falls faster than the variation of CS. The divergent trends in the CV for CS and PS imply additional trade-offs among stakeholders associated with this policy. In general, regional diversification of production does not represent a favorable policy option if production efficiency in the new region declines as indicated here. The only benefit is reduced CV of PS from spreading the production risk across multiple regions. Consumers do not benefit because less efficient production implies higher prices and more volatility in CS.

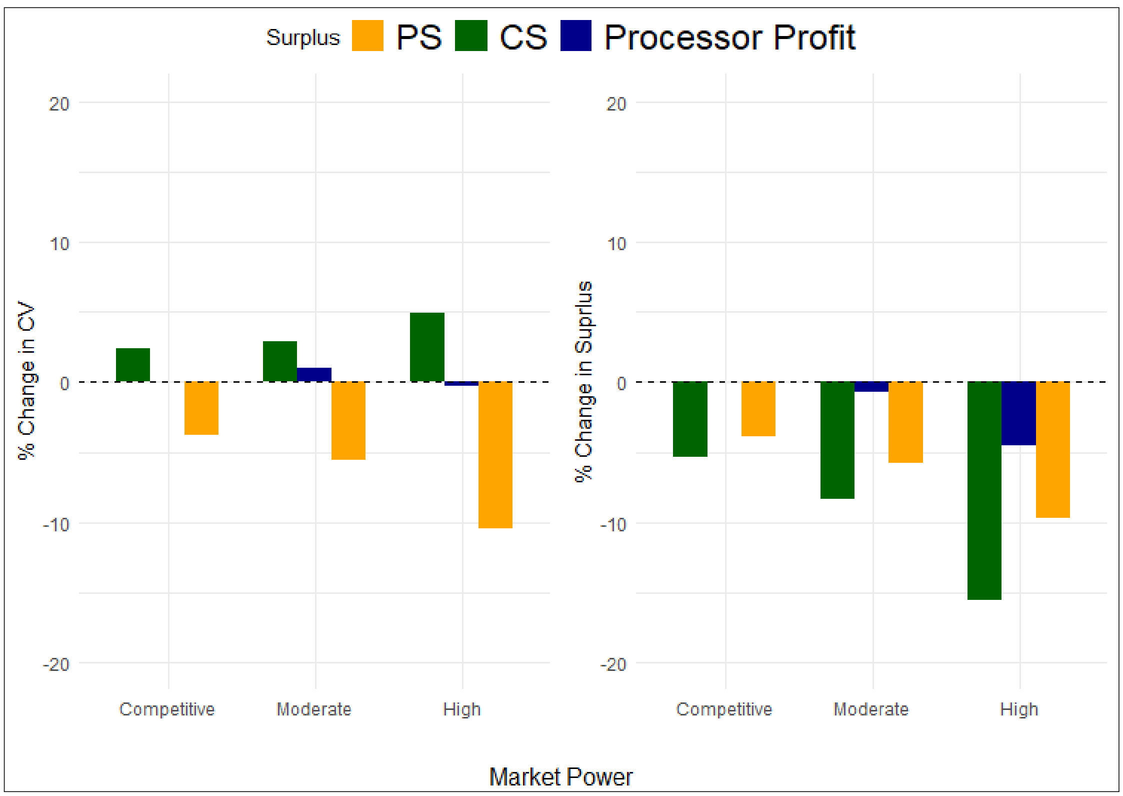


Figure 9: Impacts of adding a production region to diversify risk.
Note: Authors' creation from numerical simulations. The vertical axis measures the % change of moving from a single production region to two. The results show resilience benefits to producers, but reduction in mean surplus for all agents. Processor profit is omitted from the competitive case because it is zero in each instance.

5 Conclusion

Experiences of coping with food supply chain disruptions due to COVID-19 and the Russia-Ukraine conflict, as well as the recognition that extreme events are likely to become more common moving forward, have spurred interest in food supply chains and policies to improve their resilience. This paper has studied the efficiency and resilience impacts of four of the most prominent strategies being discussed or already being implemented in the US.

Our supply-chain model allows for any representation of market competition ranging from perfect competition to pure monopoly/monopsony. This model flexibility is very important in studying market resilience because market power of intermediaries has often been blamed for supply chains' lack of resilience, and strategies to enhance food markets' competitiveness have been at the forefront of policy discussions. A key innovation of our model framework is its recognition that extreme events are likely to introduce correlated shocks within a supply chain. We show that market disruptions from extreme events are more severe the greater is the correlation of positive shocks to consumer demand and negative shocks to farm supply and processing capacity.

An essential contribution of our work is the quantification of the impacts of proposed policies on resilience under extreme shocks, as measured by the coefficient of variation of market surplus earned by each group of supply-chain participants, and market efficiency, as measured by the average market surplus achieved under the policy for each participant. The efficiency-resilience trade-off is crucial to the evaluation of proposed policies because the popular belief is that the quest for efficiency has caused supply chains to become less resilient.

Results of the simulation analysis yield key insights regarding the proposed policies. Policies designed to stimulate competition among market intermediaries have the potential to yield win-win outcomes for farmers and consumers because they transfer market surplus to them and also reduce the variability of returns under extreme shocks.

Stimulating entry of processors is most effective in supply chains with high market power. Farmers and consumers benefit from significantly higher market surplus and lower variability of surplus in these settings. Benefits of entry are much more limited in settings that are already highly competitive or if entrants are unable to reduce the exercise of market power by incumbent processors.

The impacts of anti-price-gouging laws also depend critically on the competitive conditions of impacted supply chains. In competitive markets, restrictive price caps can be highly damaging, reducing consumer and producer surplus through restricting production and creating shortages at the restricted price, and also increasing the relative variability of surplus. The laws can be effective when imposed in less competitive markets, where they can increase market output without causing shortages. However, these laws generally reduce resilience to consumers and producers under extreme shocks, creating a trade-off between resilience and efficiency. Because anti-price-gouging laws apply widely in emergency situations. Their overall efficacy in food markets hinges on competitive conditions across the full spectrum of markets where the laws would apply.

Diversifying production into multiple regions is unlikely to be beneficial regardless of market competition conditions if production in new regions is less efficient than in the incumbent regions. In all competitive settings considered, regional diversification reduced market surplus for all participants due to inefficiencies created in shifting production to less efficient regions and raising processing costs due to reduced exploitation of size economies. Regional diversification produced generally small and mixed effects on variability of returns, reducing variability for producers and increasing it for consumers.

Though we focus on welfare impacts of policies under extreme shocks, it is worth noting that three of the four policies studied impact supply chains during normal times. The anti-price-gouging law is the only policy that activates during emergencies stemming from such extreme events. More competitive supply chains, whether due to stricter enforcement of anti-trust laws or subsidization of entry by new processing firms, benefit farmers and consumers during normal periods and supply the added benefit of being more resilient to extreme events. However, diversifying production into new, less-efficient regions reduces market surplus for all supply-chain participants in normal periods, too, and produces mixed returns to resilience under extreme events. Weighing the effects on agents along the supply chain, in anticipation of future extreme events, ultimately determines the effectiveness of these policies.

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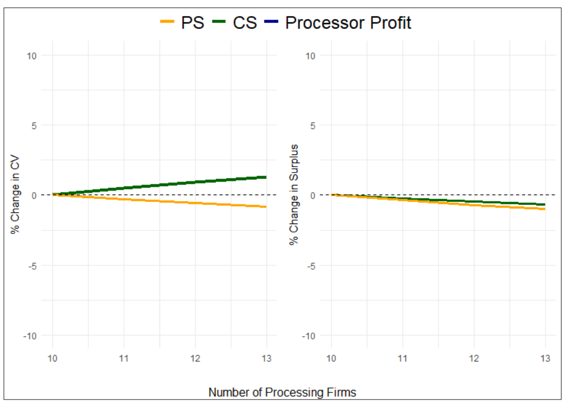
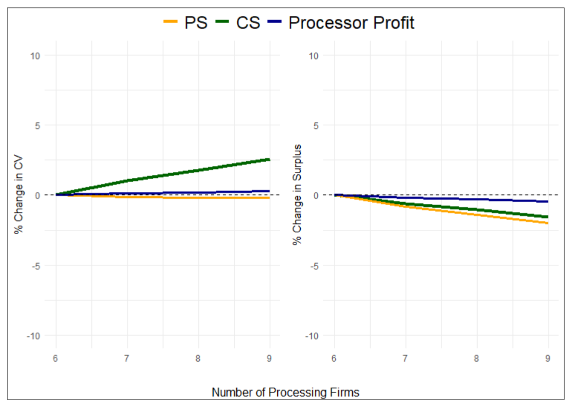
Appendix

A Processor Entry with No Market Power Effect

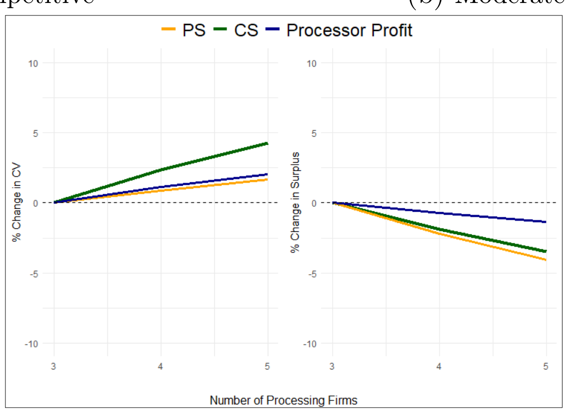
The main text studied processor entry for a setting when entry reduced processor buyer and seller power. Another possibility is that entry, especially by small-scale processors, does not impact the market power of incumbent firms. Figure A1 depicts impacts on CV and mean surplus for this case. When market power is held constant, the economies of size penalty from entry unequivocally reduces average welfare outcomes for all agents. There is a small resilience gain for producers when the market power is low (i.e., N is large). The CV for PS decreases when N is large because the variance of PS falls faster than the mean PS. The variance of PS decreases due to spreading production shocks over a larger number of plants. These results show that the resilience and efficiency improvements in figure 5 largely depend on the reduced market power effect of processor entry.



(a) Competitive



(b) Moderate Market Power



(c) High Market Power

Figure A1: Impacts of Adding Processors with Constant Market Power

Note: Authors' creation from numerical simulations. Vertical axis measure the % changes relative to the baseline number of processors for each scenario.

B Anti-Price-Gouging Laws: Additional Cases

First, we illustrate a case in figure B1 where output at the price cap is less than the pre-shock equilibrium output. For both cases in figure 6 in the main text, the output supplied under a fixed price is larger than the pre-shock equilibrium output, Q^{oo}. Sellers have limited market power in figure B1, and the fixed price, $P^{r,oo}$, intersects the new PMC curve (PMC') at output $Q^{s,oo'}_{fix} < Q^{oo}$. The market shortage is $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$. The welfare impacts of the shortage under random allocation of limited supply are the same as discussed in the main text.

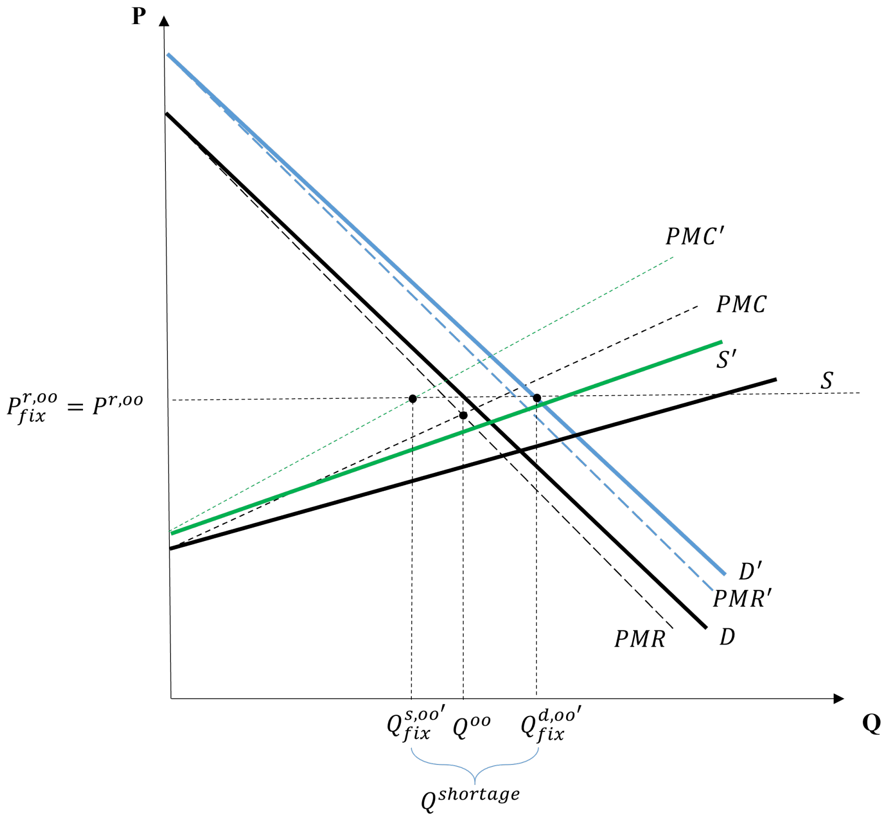


Figure B1: Fixing the Retail Price under Limited Seller Power

Second, we discuss the impact of a price ceiling imposed on the farm price instead of the retail price.[19] Figure B2 depicts this case. Absent an anti-price-gouging law, equilibrium output occurs where PMR' intersects PMC' at output $Q^{oo'}$, with farm price $P^{f,oo'}$. However, instead the farm price ceiling is set at the pre-shock level, $P^{f,oo}$. Portions of the post-shock supply curve, S', above $P^{f,oo}$ are no longer attainable. $P^{f,oo}$, thus, represents the processors' PMC for purchasing farm outputs. Processors demand $Q^{d,oo'}_{fix}$ at this price, but suppliers provide only only $Q^{s,oo'}_{fix}$. The market shortage is $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$.

[19]For example, the New York Attorney General sued Hillandale Farms Corporation in August 2020 for illegally gouging the price of eggs.

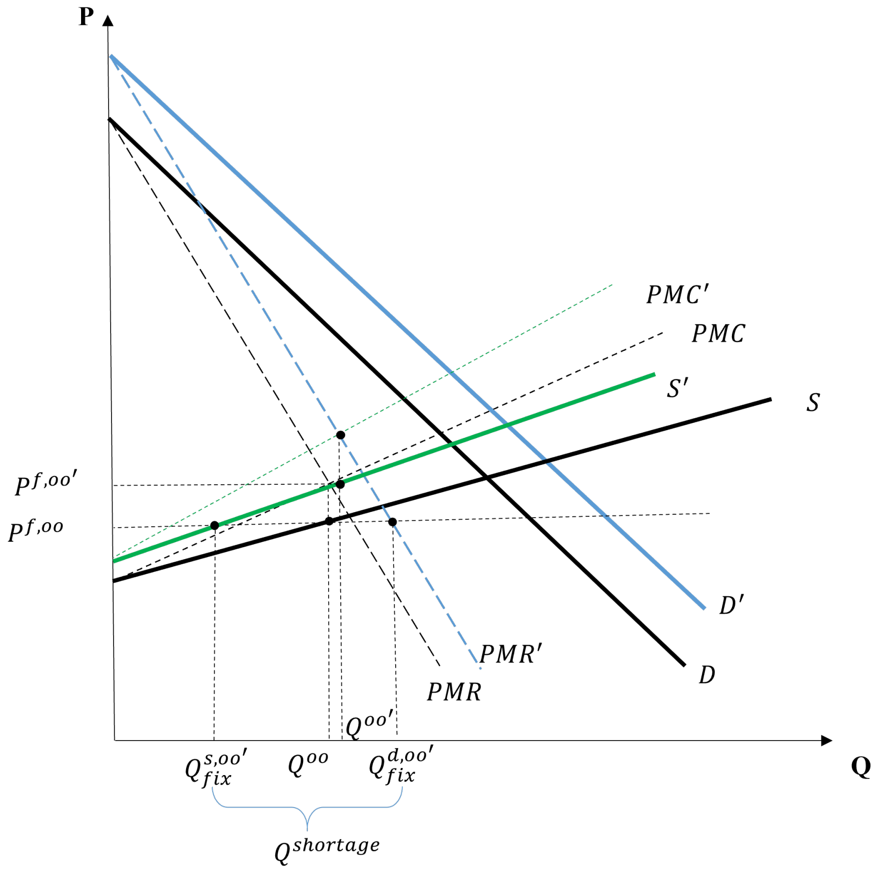


Figure B2: Fixing the Farm Price

Finally, the effect of retail price stickiness under no seller power is illustrated in figure B3. Though it shares much similarity with the cases under imperfect competition, there is no incentive for the processor to reduce the output for higher price to begin with. As a result, imposing the fixed retail price would unambiguously result in a smaller equilibrium output and a shortage of supply. The processor produces Q prior to the shocks and charges P. Post the shocks, the price is fixed at $P_{fix} = P$. This price meets the new supply curve, S', at Q^s_{fix} which is strictly smaller than Q_{flex}. The shortage of supply is $Q^d_{fix} - Q^s_{fix}$. Note that this case applies even if there is buyer power in the market because the key driver for $Q_{flex} > Q^s_{fix}$ is the lack of seller power.

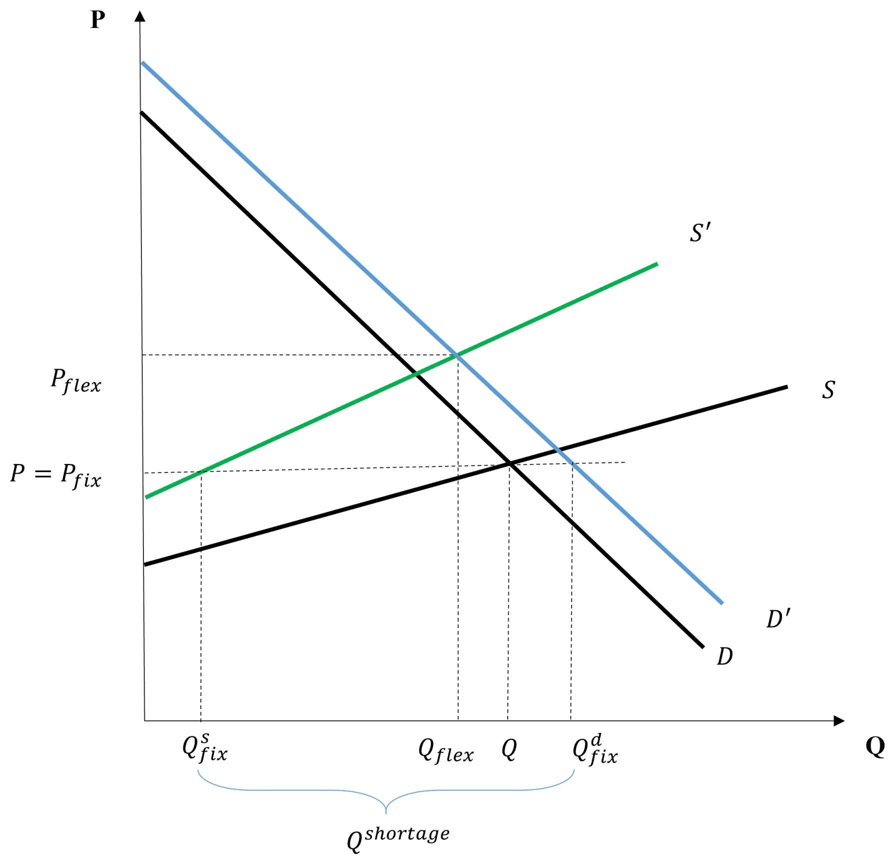


Figure B3: Fixing the Retail Price under Perfect Competition

C Coefficient of Variation and Mean Welfare Measures

This appendix develops the mathematics for the CV and mean values of PS and CS. We start with the mean CS. Recall from section 3 that the pre-shock CS equals $\frac{(a-P^{r,oo})Q^{oo}}{2}=\frac{\alpha}{2}(Q^{oo})^2$ where

$$Q^{oo}=\frac{a(1-\frac{\xi}{\eta})-b(1+\frac{\theta}{\epsilon})-c^w}{\alpha(1-\frac{\xi}{\eta})+\beta(1+\frac{\theta}{\epsilon})}. \tag{C1}$$

Shocks change a, b, β, and N and result in a new industry equilibrium output $Q^{oo'}$:

$$Q^{oo'}=\frac{a'(1-\frac{\xi}{\eta})-b'(1+\frac{\theta}{\epsilon})-c^w}{\alpha(1-\frac{\xi}{\eta})+\beta'(1+\frac{\theta}{\epsilon})}, \tag{C2}$$

where $\beta'=\frac{N}{N'}\beta$. The corresponding CS, CS', can be computed as $\frac{\alpha}{2}(Q^{oo'})^2$.

Under shocks, the percentage change in the mean CS is determined by the percentage change in the industry output as a particular parameter changes (e.g., as market power increases in figure 4). For the same reason, changes in the mean post-shock PS are also determined by changes in the industry output. Thus, in most figures, we see that the curves of changes in the mean post-shock CS and mean post-shock PS overlap.

The two curves deviate slightly in figure 5 because of a rounding issue for integers in computing $\beta'=\frac{N}{N'}\beta$. Given different values of N, the simulated $\frac{N}{N'}$ differ. In general $\frac{N}{N'}$ declines in N. The curves of changes in the mean post-shock CS and mean post-shock PS curves in figure 9 also deviate because PS is not computed using the total industry output as CS is; PS is computed using two regional outputs, respectively, and then adding up the two regional PS values.

CV equals the standard deviation divided by the mean of CS under shocks. Formally, CV of CS equals:

$$\frac{\sqrt{\sum_{i=1}^{I}(CS_i'-\bar{CS}')^2\delta_i}}{\bar{CS}'}=\sqrt{\sum_{i=1}^{I}(\frac{CS_i'}{\bar{CS}'}-1)^2\delta_i}, \tag{C3}$$

where I is the number of simulation iterations, δ_i is the probability of each CS_i', and the δ_i add up to one. The mean of post-shock CS, $\bar{CS}'$, equals $\sum_{i=1}^{I}CS_i'\delta_i$.

Intuitively, the larger the deviation of CS_i' relative to pre-shock CS, the larger is $\frac{CS_i'}{\bar{CS}'}$. Therefore, CV increases in the relative magnitude of the CS pre and post shocks. Given the parameter values, CV for CS increases in $\frac{CS'}{CS}$, which is proportional to $\frac{Q^{oo'}}{Q^{oo}}$, if $\frac{CS'}{CS}>1$. If $\frac{CS'}{CS}<1$, CV decreases in $\frac{CS'}{CS}$.

$\frac{CS'}{CS}>1$ and $\frac{Q^{oo'}}{Q^{oo}}>1$ are the typical case in our baseline simulations, in which case CV increases in $\frac{Q^{oo'}}{Q^{oo}}$ and hence increases in the ratio of:

$$R=\frac{a'(1-\frac{\xi}{\eta})-b'(1+\frac{\theta}{\epsilon})-c^w}{a(1-\frac{\xi}{\eta})-b(1+\frac{\theta}{\epsilon})-c^w}\frac{\alpha(1-\frac{\xi}{\eta})+\beta(1+\frac{\theta}{\epsilon})}{\alpha(1-\frac{\xi}{\eta})+\beta'(1+\frac{\theta}{\epsilon})}. \tag{C4}$$

Taking first derivatives and given baseline parameter values, one can show, with complex mathematics, that R rises in ξ if $a' > a$ (i.e., a positive demand shock) and $\beta' > \beta$ which echoes figure 4. The complexity of analytical expressions supports the use of simulations as employed in the main body of this study.

Similarly, given that the post-shock PS equals $\frac{\beta}{2}(Q^{oo'})^2$, one can show that CV of PS is determined by $\frac{\beta' PS'}{\beta PS}$. Because $\beta' = \frac{N}{N'}\beta$, $\frac{\beta' PS'}{\beta PS}$ moves with $\sqrt{\frac{N}{N'}}\frac{Q^{oo'}}{Q^{oo}}$. The relative resilience of post-shock CS and post-shock PS follow the same pattern as long as $\sqrt{\frac{N}{N'}}\frac{Q^{oo'}}{Q^{oo}} > 1$ and $\frac{Q^{oo'}}{Q^{oo}} > 1$. If $\sqrt{\frac{N}{N'}}\frac{Q^{oo'}}{Q^{oo}} < 1$ and $\frac{Q^{oo'}}{Q^{oo}} > 1$, the patterns of CV for CS and PS differ.