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

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Abstract

Recent extreme events and the disruptions they have caused have made supply-chain resilience a key topic for researchers and policy makers, especially in the food industries. This paper provides a theoretical and simulation framework to assess the resilience and welfare implications of three key policy responses that either are being implemented or are under consideration. Specifically, we study the ramifications of market power, the entry of additional processing capacity, and price gouging laws. We show that, while there are some gains to resilience from these policy measures, the effectiveness of these policies depends heavily on the existing market structure, and resilience gains come at the expense of efficiency.

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1 Introduction

The COVID-19 pandemic and the supply-chain disruptions it caused have motivated researchers and policymakers to assess the resiliency of food supply chains and to search for opportunities to make them more robust to the risk of future extreme shocks (FAO, 2021; U.S. Department of Agriculture, 2022). In addition to pandemics, extreme shocks can emanate from a variety of sources, including 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 processor shutdowns and inability to harvest some crops due to labor shortages (Martinez, Maples, and Benavidez, 2020; Lusk and Chandra, 2021).

The experience with COVID-19 has made building more resilient supply chains that adapt quickly in the presence of extreme events a clear policy goal for the U.S. and other economies. Resilience in food-supply chains for most economies implies an ability to sustain food production and consumption without undue reliance on international trade because catastrophic events are likely to curtail trade due to disruptions in transportation networks and/or country bans imposed on exports and imports.[1] Indeed, federal and state policymakers have already introduced several measures intended to enhance the resilience of U.S. food supply chains, such as subsidizing entry of new processing firms, stepped-up enforcement of competition laws, supporting local and regional food systems, and outlawing profiteering or

[1]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 imposed for the invasion. Meanwhile, other countries imposed export restrictions due to rapidly rising prices for key commodities. Examples include Indonesia, the world's largest exporter of palm oil, banning exports of palm oil in response to rising domestic prices and India banning wheat exports. Another contemporaneous example of export bans exacerbating food shortages and rising food prices is the escalation of world grain prices in 2007-08 that led to restrictions or bans on grain exports in Argentina, India, Kazakhstan, Pakistan, Ukraine, Russia and Vietnam (Mitchell, 2008).

"price gouging" in response to severe market disruptions.

This paper seeks to evaluate the effectiveness of key policies that have been implemented or proposed with the goal of creating more resilient agricultural supply chains. 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).

Agricultural supply chains have evolved through the quest for production efficiency and cost savings, but the common perception is that the most efficient food supply chain structures may be the least resilient (Viswanadham and Kameshwaran, 2013; Hobbs, 2021; U.S. Department of Agriculture, 2022),[2] 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 focus upon policies that have been adopted or discussed in the U.S. and calibrate the model to U.S. 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 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 second key innovation of our model relative to others is that we incorporate explicitly that most extreme shocks, whether due to wars, pandemics, or natural disasters,

[2]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).

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 calibrate the model based on contemporary data and recent empirical research for the U.S. to represent prototype supply chains for key staples. We then utilize Monte-Carlo simulations to examine the impacts of different extreme 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) of welfare outcomes across a large number of simulated shocks. We show the importance of considering the simultaneity of these shocks across the supply chain in future analyses of market resilience.

We utilize the calibrated model and simulation framework to study three primary policy questions 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 markets in response to extreme shocks. On January 3, 2022, the Biden Administration announced plans for stepped up enforcement of antitrust laws in the meatpacking industries. In addition, the U.S. Congress has introduced legislation known as the Meat and Poultry Special Investigator Act of 2022 to give the U.S. Department of Agriculture (USDA) authority to investigate competition issues in the meat and poultry industries. USDA itself has announced plans to partner with the U.S. 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 welfare outcomes of consumers, marketers, and farmers in the event of catastrophic shocks. As noted, subsidization of entry into meat processing is a key policy response being undertaken in the U.S. Entry of processors spreads the shutdown risk across a greater number of firms, but for a given regional supply function for the farm product, more processors implies lower throughput per firm, generating higher costs in the presence of scale economies.

Third, we study the ramifications for market resilience of price rigidity imposed along the supply chain. Price rigidity is common in modern supply chains due to fixed prices specified via contracts,[3] and, in addition, price controls are often also imposed as a policy response to significant market shocks, including anti-price gouging laws,[4] or *ad hoc* price controls imposed by politicians under emergency authority.[5] While these price limits prevent extreme price shocks to consumers, they also may exacerbate shortages of products and cause heterogeneous welfare effects by limiting market participants' abilities to adapt through a price mechanism to changing market conditions. We show, furthermore, that price fixity may inhibit intermediaries' exercise of seller power and under certain conditions can cause higher output without shortages compared to the flexible-price case.

We find that while these policies reduce relative volatility of welfare outcome for farmers and consumers, the marginal impact on resilience and efficiency depends largely on the context of the market structure. Agriculture and food supply chain policy aimed at increasing resilience must carefully assess the probabilistic nature of extreme events and the related efficiency tradeoffs. This paper complements a growing body of qualitative food supply chain analyses with a theoretical framework

[3]Fixed prices for one-to-two years in duration are common in contracts between retailers and food manufacturers, and fixed prices are also a feature of some farm production contracts (Spalding et al., 2022).

[4]Thirty seven U.S. states presently have price gouging laws that engage during natural disasters or declared emergencies (Morton, 2022), and such laws were triggered in a number of jurisdictions in response to the pandemic.

[5]For example, during a declared emergency, California legislative code precludes price increases of more than 10% above pre-emergency levels, unless a person can prove that a greater price increase is "directly attributable" to higher costs due to the emergency.

2 Extreme Events

The occurrence of the COVID-19 pandemic and the Russia-Ukraine conflict in close succession and the disruptions they have caused have brought heightened awareness to the potential vulnerability of food-supply chains to such extreme events. 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 environments that are changing rapidly, expanding contacts between humans and wildlife, and accelerating the potential for pandemic events (Allen et al., 2017; Wolfe, Dunavan, and Diamond, 2007; Jones et al., 2013).

A consensus has also emerged that climate change is associated with increasing incidence and intensity of severe weather events, including extreme temperatures (both hot and cold), extreme precipitation, and drought (Cornwall, 2016; Wuebbles et al., 2014). Finally, the destructive capacity of armed conflicts is exacerbated by modern conventional weaponry, as well as the risk of introduction of chemical or biological weapons onto the battlefield. Table 1 outlines three categories of extreme events and their potential impacts on agents along the food supply chain.[6]

3 Model

We consider a closed-economy model of a supply chain containing farm production, processing and retailing, and consumption.[7] Intermediaries may exercise buyer power over farmers

[6]The list of extreme events in table 1 and potential impacts is intended to be illustrative. The magnitude of shocks will vary widely depending on specific contexts. Note that we make no attempt to study the most extreme "extinction" events that could occur, such as nuclear conflict or asteroid or comet impact with Earth. Such events are predicted to have severe and long-lasting impacts such that coping with them would require massive stockpiling of food reserves, which is not considered in this model.

[7]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 U.S. and calibration to U.S. data. Over 87% of food

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	Negative: reduced yields	Positive: Stockpiling prior to extreme weather	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 threaten 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 shutdown due to the COVID-19 pandemic.

and seller power over consumers. 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 quantities produced at every stage of the chain can be equalized given appropriate measurement units. Hereafter, the industry output is denoted by Q at any stage of the supply chain.

To simplify exposition in model development, we assume $n = 1$ production region in the base model. The model is later extended to incorporate multiple production regions, i.e., $n > 1$, as a resilience 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.

We assume N homogeneous processors in the region. Domestic processors collectively face a national demand for the retail product.[8] Let c^r denote a constant marginal cost for retailers. The wholesale demand for the processed product is then:

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

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 profit-maximizing processor j choosing the output q_j is:

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

where $C^w(q_j)$ is the total cost of processing for processor j. Economies of scale/size inherent

consumed in the U.S. is produced domestically according to the USDA.

[8]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.

in processing costs will be important in assessing the resilience versus efficiency trade-offs. We assume that all processors have access to the same technologies and, thus, this cost function is common to all processors.

Given that processors are homogeneous, we have symmetry in 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):

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

where $c^w = \frac{\partial C^w}{\partial q}$ represents the marginal costs of processing for the processor, $0 \leq \theta \leq 1$ is the processor's buyer power parameter, $0 \leq \xi \leq 1$ is the processor's seller power parameter,[9] $\eta > 0$ 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 of the expression 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.

[9] For simplicity of exposition, we model seller power as emanating from processors, but the qualitative impact on market behavior is identical if the seller power is exercised by retailers.

3.1 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 function be:

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

and let the market demand function be:

$$P^w(Q) = (A - \alpha Q) - c^r = a - \alpha Q. \tag{6}$$

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

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

Consistent with the model formulation, we specify locally constant marginal costs, c^w, but allow marginal cost to be a function of the number, N, of processing firms. Equilibrium output of each processing firm is decreasing in the number of symmetric firms operating in normal times. Thus, $c^w = \frac{\partial C^w}{\partial N} > 0$ reflects economies of scale, and $\frac{\partial C^w}{\partial N} = 0$ represents constant returns to scale.[10]

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:

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

[10]We do not consider specifications to reflect diseconomies of size because there is no empirical support for it.

The equilibrium wholesale and farm prices are obtained by plugging Q^c into the wholesale demand and farm supply functions, respectively. Similarly, we can find equilibrium output and prices under imperfect competition. The first-order condition becomes:

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

The left-hand side of the equation represents the PMR for the representative processor, while the right-hand side represents the PMC of acquiring the farm product. Given symmetry among processors, this optimization condition can be solved along with the farm supply and wholesale demand functions to derive the market's oligopoly-oligopsony equilibrum output:

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

where $Q^c > Q^{oo}$ for all positive ξ and θ, and Q^{oo} decreases in ξ and θ. The output per firm is $q^{oo} = \frac{Q^{oo}}{N}$. The equilibrium wholesale price is $P^{w,oo} = a - \alpha Q^{oo}$, 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 $\frac{1}{2}(a - P^{w,oo})Q^{oo}$, producer surplus (PS) equals $\frac{1}{2}(P^{f,oo} - b)Q^{oo}$, and processor profits is $(P^{w,oo} - P^{f,oo} - c^w)Q^{oo}$. The dead-weight-loss (DWL) from market power is given by $\frac{1}{2}(P^{w,oo} - P^{f,oo})(Q^c - Q^{oo}) - c^w(Q^c - Q^{oo})$.

3.2 Measure of Resilience

Although researchers have used the variance (or standard deviation) of a variable or welfare measure of interest, e.g., industry-level output or CS, to measure volatility under a given shock (e.g., Ma and Lusk (2021)), to gauge the resilience–efficiency trade-off. However, to compare the volatility of several random variables with different mean values variance and standard deviation are not the most appropriate measure. The coefficient of variance (CV) is the most appropriate measure of relative dispersion (Curto and Pinto, 2009).

CV is the standard deviation of a variable divided by its mean Brown (1998). It provides a dimensionless measure of relative volatility. The CV 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). For 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 different agents, who have different average surplus measures, and across market parameter values within a simulation. CV, therefore, serves as a proxy for market resilience, capturing the stability of agents' welfare under system-wide shocks.

3.3 Parameterization

To parameterize the model, we normalize the risk-free, competitive equilibrium industry-level output to 1.0. The corresponding equilibrium wholesale price on the national market is $a - \alpha Q^c$ and also normalized to 1.0. The equilibrium retail price is $1 + c^r$. 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, N of processors. This farm price is the farm share of the normalized wholesale 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.

Capturing the presence of economies of scale in processing is critical in our model because various policies to promote resilience rely upon promoting entry of additional processors, typically small/medium-sized ones, or diversifying production into multiple regions. Economies of scale in food processing have been studied most extensively for the meatpacking industries, wherein scale economies have generally been found to exist and to be substantial.

Paul (2001) shows that the cost function for U.S. 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 $g < 1$ denoting the presence of scale economies. Paul (2001) reports estimates of $g \approx 0.95$ for U.S. beef processing. MacDonald and Ollinger (2000) report a nearly identical cost elasticity estimate for U.S. hog processing. Ollinger, MacDonald, and Madison (2005) found even greater scale economies for U.S. poultry, with the cost elasticity estimates for chicken ranging from 0.883 to 0.925, with the greater scale economies associated with larger plants. Somewhat greater scale economies were found for turkey processing.[11]

To adapt these scale economy estimates to our model structure, we express marginal processing costs as $c^w = c(N)^\gamma$, where $\gamma \geq 0$, and equate this expression to marginal cost in Morrison Paul's model to solve for γ. Here $\gamma = 0$ denotes constant returns to scale, while $\gamma > 0$ indicates the presence of economies of scale. Given that the equilibrium output per homogeneous plant under perfect competition is $q^c = \frac{1}{N}$, we have:[12]

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

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

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

Equilibrium solutions to the model then depend on the six parameters (η, ϵ, f, g or γ, ξ, and θ) describing the market structure and three exogenous shifters that represent alternative shocks to the supply chain. We assigned base values for these variables from the

[11]Devarajan and Rodrik (1989) allow for even greater economies of scale, with $g \approx 0.8$, in their study of trade liberalization in developing countries.

[12]Note that we generalize this cost function to allow additional of production regions, $n > 1$. Prior model simplifications assumed $n = 1$.

empirical literature of the supply chain for meats, and these values displayed in Table 2. We show the simulation results for other product markets in the appendix.

Parameter	Description	Value	Source
η	|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	0.88-0.95	(Paul, 2001; Ollinger, MacDonald, and Madison, 2005)
γ	Economies of scale parameter	$1-g$	Authors' calculation
ξ,θ	market power parameters	0, 0.15, 0.3	(Sexton and Xia, 2018)

Table 2: Baseline Parameter Values for Simulation

3.4 Correlated Shocks

As noted, a distinctive feature of this paper is that we consider correlation in shocks to the supply chain. 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. These events simultaneously positively shock demand due to consumers attempting to stockpile goods. Catastrophic events that cause significant loss of life and/or recession could result in a negative demand shock.

To illustrate correlated shocks between retail and processing stages, figure 1 displays weekly beef slaughter and retail sales for the first half of 2020. The initial weeks of the COVID-19 pandemic induced panic buying and hoarding of available supplies, and, at the same time, forced multiple processing plants to stop operations due to employee illnesses.

Accounting for multifaceted and simultaneous shocks plays a vital role in the assessment of food supply chain resilience because most conceivable extreme-event scenarios trigger are likely to cause similar market-altering events. Yet, a gap exists in the literature for food supply chain resilience that incorporates this facet of extreme events (Davis, Downs, and Gephart, 2021).

Multi-variate joint distributions (or copula) allow for random variables drawn from

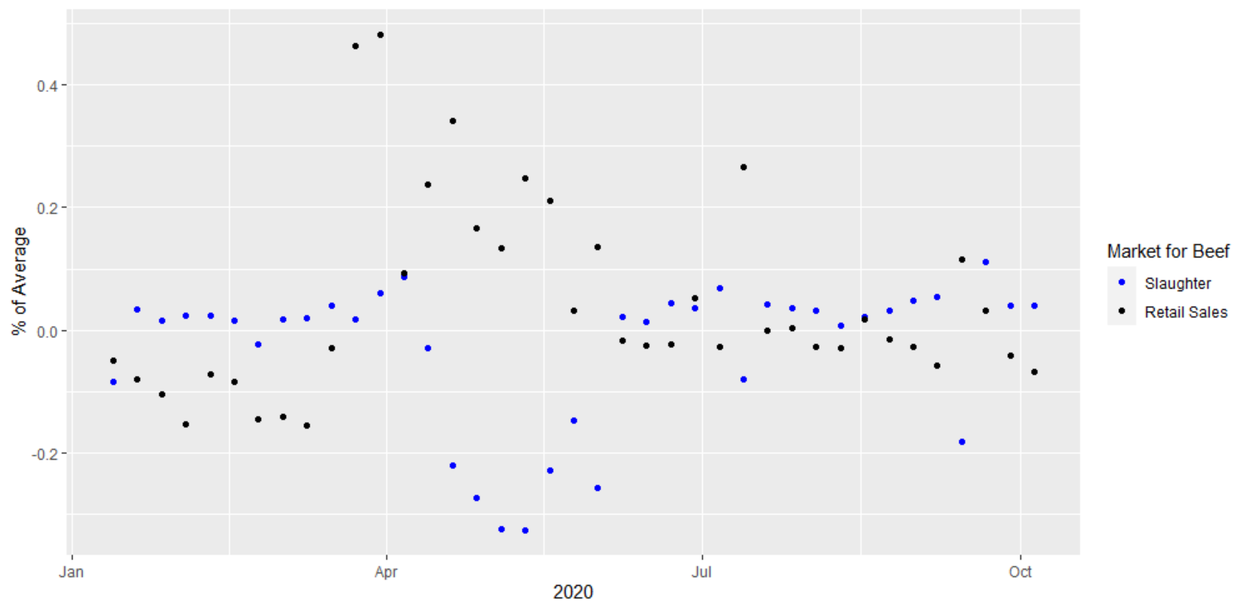


Figure 1: Weekly Beef Slaughter and Retail Sales relative to Average.

differing distributions with dependant structures.[13] For supply chain analysis of extreme events, copulas allow for draws of random variable shocks from a positive/negative half-normal parallel demand shock (σ), negative half-normal parallel supply shock (μ), and binomial processor shutdown shock (N').

$$\begin{aligned} \sigma &\sim H(\theta_H = 5) \\ \mu &\sim H(\theta_H = 10) \\ N' &\sim B(N, 0.75) \end{aligned} \tag{14}$$

Table 1 informs the parameterization of these distributions according to the possible magnitude of extreme events in percentage terms. The half-normal parameters (θ_H) correspond to a mean 20% shift in demand and 10% farm supply shift.[14] The binomial shutdown shock determines the number of processing plants that remain operable, N', from a total number of processors, N. On average, 75% of the processors remain operable after an extreme event. These shocks should not be taken as precisely estimated magnitudes for all

[13]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).

[14]The mean and variance of a half-normal distributions are specified by a single scale parameter value.

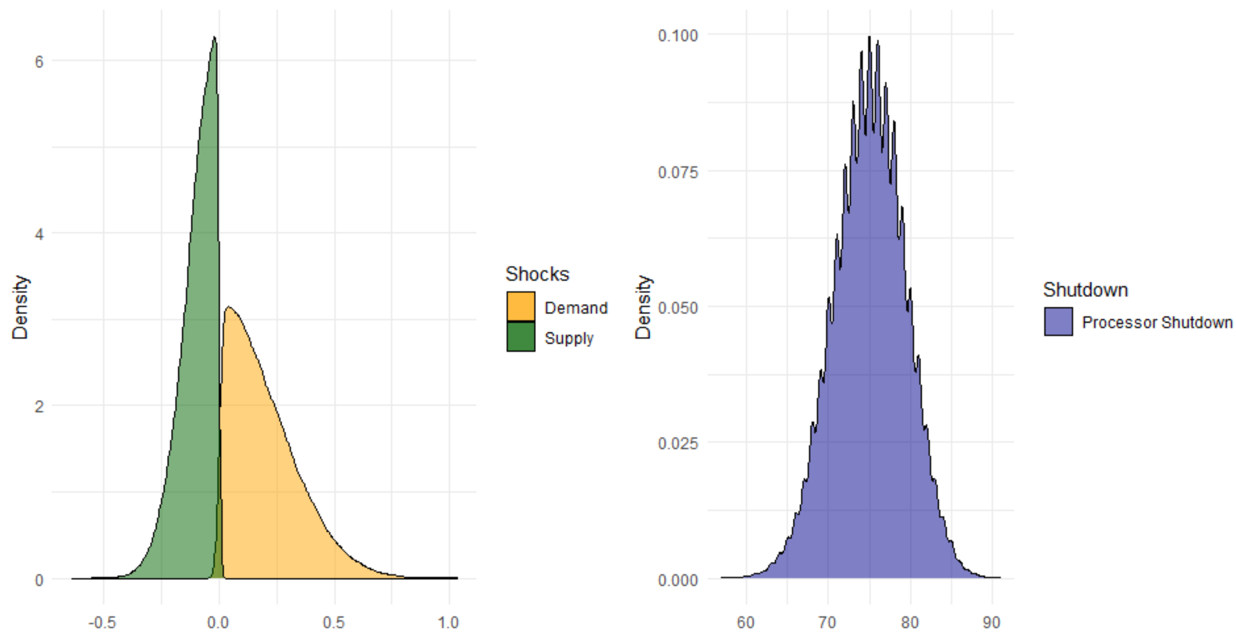


Figure 2: Simulated Shocks

extreme events but are emblematic of recent experiential evidence. The densities of each shock for our simulations are presented in figure 2.

We draw 100,000 shocks from the multi-variate joint distribution, allowing for correlation of shocks across farm supply, processing, and consumer demand, spanning the range of these possible effects. The dependant nature 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. Given values for each element of the covariance matrix, we draw 100,000 shocks from a copula distribution, and compute unique equilibrium outcomes and welfare measures.

To illustrate the importance of the degree of correlation between the shocks, we simulate over the off-diagonal elements the covariance matrix for $\rho \in [0, 0.5]$, increasing the intensity of correlation between supply chain stages. Figure 3 displays a baseline simulation for a perfectly competitive market for alternate values of ρ. Increasing the correlation between demand and supply shocks increases the relative variance or 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.[15] Note that the the formulae for CV of CS and PS and percentage changes in mean CS and PS relative to pre-shock means are mathematically identical in this model. See Appendix B for details. Therefore, in figure 3 and other figures we use a single curve to depict the CV for both CS and PS.

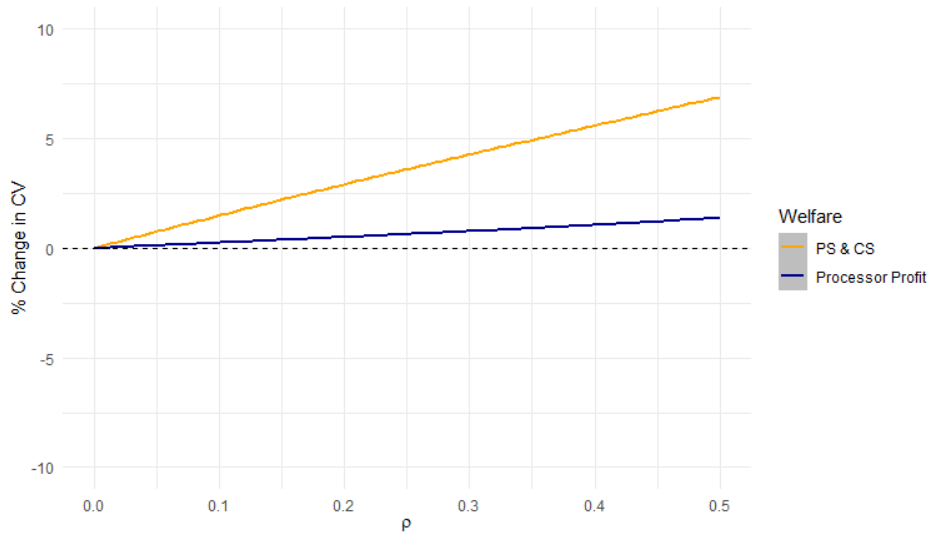


Figure 3: Correlation Between Shocks at Different Supply Chain Stages

3.5 Post-Shock Equilibrium

When processors experience a shutdown shock (i.e. N falls to N'), we assume that the market power parameters stay unchanged. At the same time, consumer demand and farm supply curves also shift. We introduce supply and demand shocks as parallel shifts, such that $a' = a(1 + \sigma)$ and $b' = b(1 + \mu)$. We assume that plants can adjust outputs to respond to the new consumer demand and farm supply functions after a shock occurs:[16]

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

[16] Although plants can adjust output in response to supply and demand shocks, they are unable to absorb farm production from plants that are shuttered due to an extreme event. This specification reflects realities of the COVID-19 pandemic in the U.S. when an estimated 700,000 hogs per week could not be processed due to plant closures, with most euthanized as a result. Inflexibility of processing is a reality of modern agricultural markets wherein processors utilize procurement contracts to ensure that their facilities are operating at efficient capacity during normal times (Sexton, 2013). The contracts themselves bind a producer to a particular processor and also represent an impediment to timely reallocation of product in the event of plant closure.

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

After plant shutdown, final market output in a given period is equal to $Q^{oo'}\frac{N'}{N}$. The new equilibrium output may be larger or smaller than pre-shock Q^{oo} depending on a', b', and N'.

4 Simulations

We study three widely discussed policy responses that aim 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, and 3) limiting consumer price increases through anti-price gouging laws

We simulate each policy proposal and report its impact on mean economic surplus and the relative volatility of surplus (i.e., CV) for farmers, consumers, and market intermediaries. We present the results for the latter four policy interventions for three 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.[17]

4.1 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). Much less is known

[17] Although our market power parameters are not tied to a particular form of competition, it is useful to relat them to noncooperative 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 U.S. Department of Justice (DOJ) 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 U.S. beef and pork industries (U.S. Department of Agriculture, 2022).

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). The right panel displays the well-understood result that, as intermediary market power increases, consumers and producers lose economic surplus and intermediaries capture additional profits.

Less understood, however, is that CV for consumers and farmers increases in the degree of intermediary market power, while processors' CV declines over most of the range of market power simulated. Both the standard deviation of surplus and its mean value for farmers and consumers decline in the level of processor market power, but mean surplus declines faster than the standard deviation, causing CV to rise.[18] Appendix B provides a formal derivation to show that CV for farmers and consumers is increasing in intermediary market power for positive demand shocks and negative farm supply shocks.

These findings demonstrate that consumers and farmers may benefit from both higher average economic surplus and reduced variability of surplus in the presence of correlated economic shocks from policies to induce more competitive supply chains.

4.2 Entry of Processors

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

[18] 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.

[19] 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 input prices.

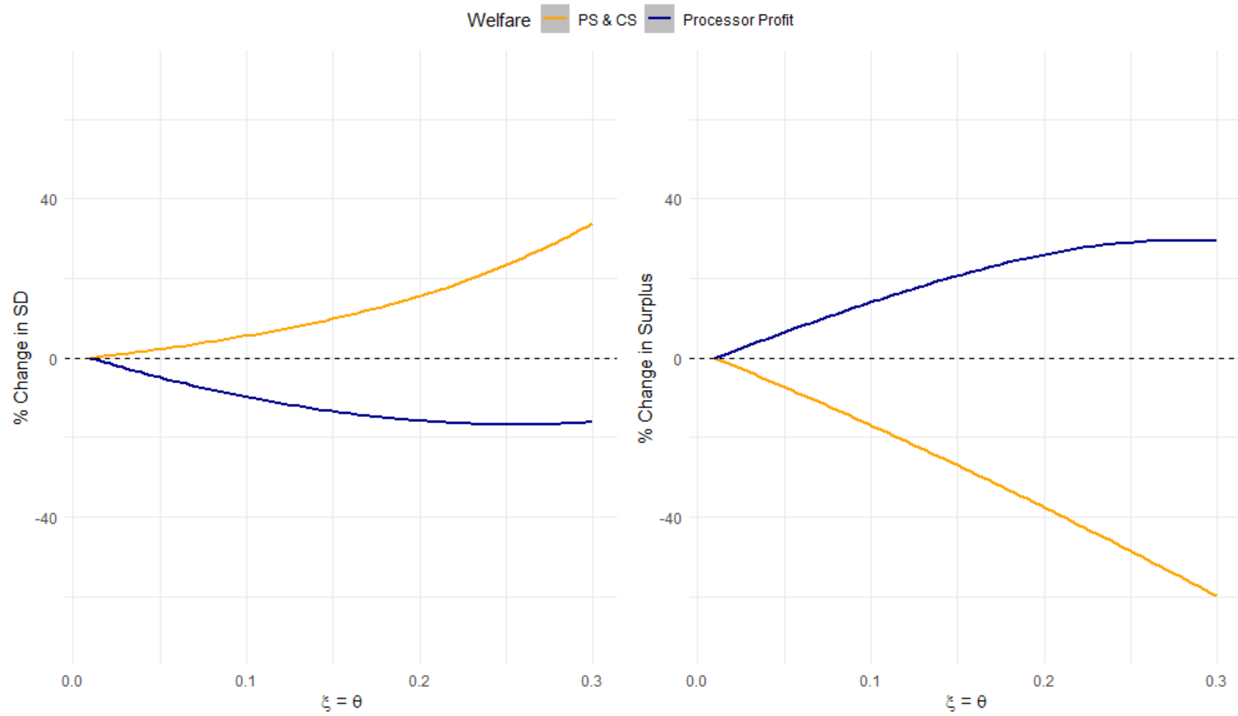


Figure 4: Impact of Increasing Intermediary Market Power on Resilience and Welfare

shutdown risk.[20]

The potential resiliency improvements from new processing entrants are twofold. First, additional processors disperse shutdown risks over a larger number of operations, thus spreading the risk of loss of processing capacity and reducing variance in industry output. Second, additional processors potentially increase competition among processors, which, as figure 4 demonstrates, increases average surplus to farmers and consumers and decreases the CV for surplus.

The main focus of the U.S. 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 is conservative in the sense of not imputing cost penalties to entrants due to small scale and also allowing the entrants to expand market competition in ways that small-scale entrants may be unable to accomplish.[21] Counterbalancing the enhanced

[20] An additional $150 million was allocated to existing small processors to remain in the marketplace and expand capacity.

[21] For example, small food processors may only serve local or regional markets, leaving national concen-

resiliency and reduced market power from adding processors is that per plant throughput declines as more processors are added for a given farm supply function, meaning that firms are less able to exploit the available economies of scale and creating a trade-off between economic efficiency and resilience.

We simulate adding processors for each of the three market competition scenarios. We assume that market power parameters are dependant on N, reflecting non-cooperative Cournot competition, such that $\xi = \theta = \frac{1}{N}$. For the competitive scenario, we begin with $N = 12$ processors and sequentially add processors to reach $N = 18$.[22] Similarly, the moderate market power case begins with $N = 6$ processors and adds entrants sequentially, while the high market-power case begins with $N = 3$ and adds entrants.

For each value of N, we simulate 100,000 positive demand shocks, negative farm production shocks, and binomial processing-plant shutdown shock that are correlated with demand. 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 perfect competition, moderate market power and high market-power, respectively.

Similar to figure 4, panels (b) and (c) show that higher levels of market power are associated with higher volatility relative to average welfare (i.e., market power as well as CV fall in N). Additionally, CS and PS rise as market power diminishes and the efficiency improvements are greater for small values of N. That is, returns from adding N are decreasing in the initial N.

Panel (a) shows total CV and share of surplus for each agent for the competitive case.[23] The impacts of adding processors on resilience and efficiency are negligible with many processors. It is interesting to note, however, that contrary to the risk-free case, processors earn positive profits with shutdown risk under competition. Positive profits are

tration largely unaffected.

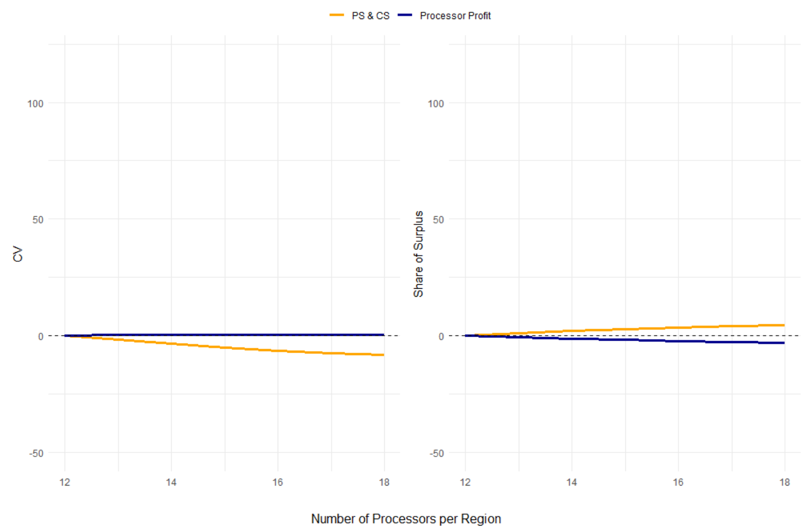
[22]For true perfect competition $\xi = \theta = 0$. However, assuming non-cooperative Cournot competition, we begin with N sufficiently high such that there are negligible marginal market power impacts.

[23]Note the y-axis change relative to panels (b) and (c). We show absolute measures for the competitive case since the percent changes are less half of one percent for each additional N.

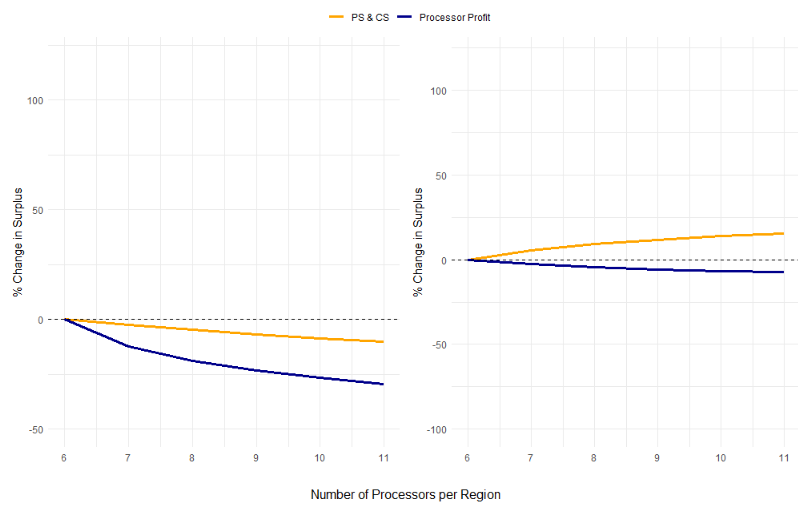
earned by active plants post-shock because they effectively produce at a level lower than Q^c due to lost capacity and are able to receive a price higher than the marginal cost.

The simulations results lead to two relevant policy conclusions. First, while there are potentially large resilience improvements from processor entry in markets with very few processors, these marginal improvements diminish as the baseline number of processors increases. Thus, stimulating entry is most effective in enhancing resilience when it is done in markets with low N ex ante.

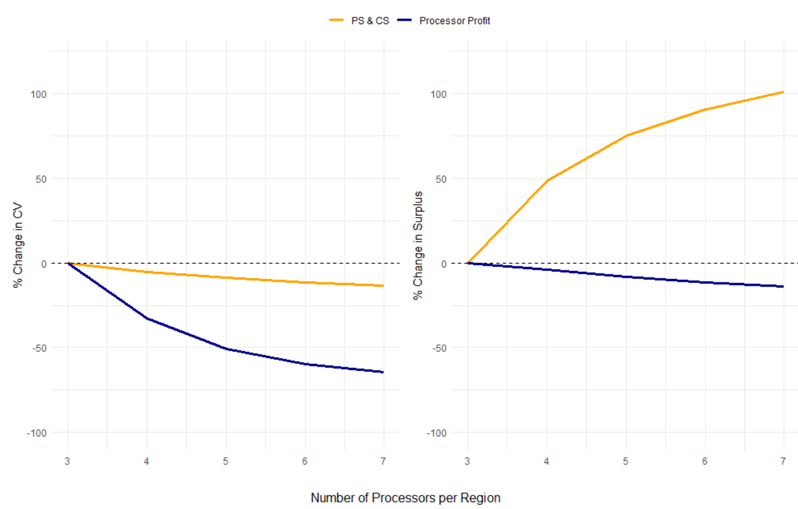
Second, for the processing sector as a whole, additional processing capacity provides resilience as processors are more equipped to capture the additional rents when extreme shocks occur. Figure 6 displays the density of processor profits across simulations for the competition case. Processors actually earn positive profits in perfectly competitive markets, stemming from the consequences of shutdown risk. Without shutdown risk, profits in the perfectly competitive case are always zero. When shutdowns occur, the remaining operable plants charge prices above marginal costs due to this shutdown-induced scarcity.



(a) Competitive



(b) Moderate Market Power



(c) High Market Power

Figure 5: Increasing Resilience from Adding Processors and Reducing Market Power

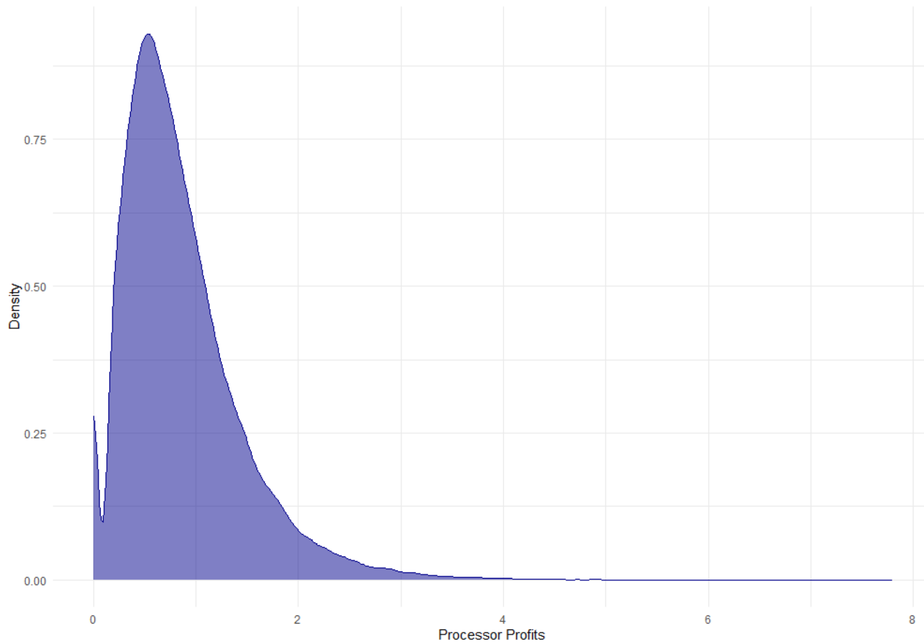


Figure 6: Density of Processor Profits under Perfect Competition with Shutdown Risk

4.3 Price Rigidity

Most U.S. states and some cities have anti-price gouging laws in place, which limit price increases that may be imposed during severe market disruptions. The goal is to protect consumers from higher prices caused by supply disruptions and demand shocks. Several price-gouging lawsuits were filed in response to supply disruptions due to COVID-19. Price ceilings may also be imposed on an ad hoc basis under emergency powers that political leaders often have. For example, price ceilings were imposed in some jurisdictions for key staples in response to the Russia-Ukraine conflict (Reuters, 2022).

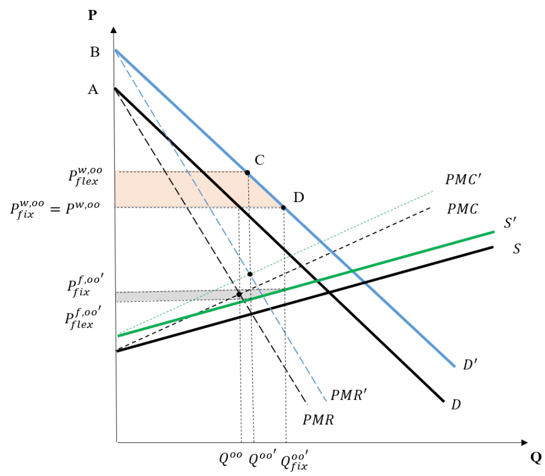
Price rigidity through contract provisions may be present in modern supply chains even in the absence of any government intervention. It is increasingly common for contracts between supply-chain participants to specify fixed prices for an extended time period. In the leafy greens markets, for example, only about 10% of transactions occur in the spot market at flexible prices, with the rest occurring through contracts of one-to-two years in duration with no or limited price flexibility (Spalding et al., 2022). Additionally, regulations and pricing structures, like the Federal Milk Marketing Orders, may cause lags in the transmission of shocks through price.

A key unanswered question, however, is how such price rigidity impacts 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 seller market power over a range of prices and, thus, may lead to increased industry output and lower price volatility.[24] This result provides an interesting contrast to binding price ceilings imposed in perfectly competitive markets, which unambiguously reduce output, cause shortages, and generate dead-weight losses.

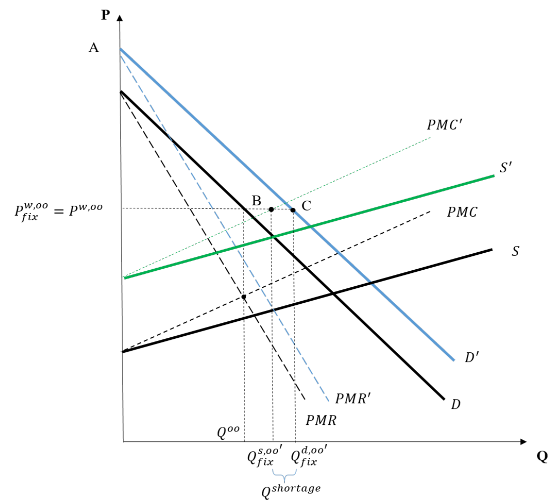
Consider the case where retail and wholesale prices are fixed at the risk-free (pre-shock) levels or some modest increment above them. The pre-shock retail price is $P^{r,oo}$ and the wholesale price is $P^{w,oo} = a - \alpha Q^{oo}$ as specified in equation (2). Shocks from extreme events shift the demand curve outward, the farm supply curve inward, and subject processors to shutdown risk. Under flexible prices, the new equilibrium quantity produced, $Q^{oo'}$, is given by equation (15) and yields the flexible wholesale price $P^w(Q^{oo'}) = P^{w,oo}_{flex}$. However, we consider that processors are limited by contract or by anti price-gouging laws to charge price no greater than $\bar{P}^{w,oo}$, where $P^{w,oo} \leq \bar{P}^{w,oo} < P^{w,oo}_{flex}$.

Here we take the tightest price bound, $P^{w,oo} = P^{w,oo}_{fix}$, to present analytical solutions. The impact of fixing wholesale price at the pre-shock level is illustrated by figure 7.

[24] Sellers with market power recognize that their sales impact the market price so that marginal revenue of incremental sales is less than price. Profit-maximizing sellers with market power accordingly sell less than a profit-maximizing perfect competitor, who equates price with marginal cost. A binding price ceiling eliminates a seller's influence over market price and can boost output.



Case 1



Case 2

Figure 7: Fixing the Wholesale Price

In case 1, the price ceiling, $P^{w,oo}_{fix}$, intersects the new demand curve, D', at $Q^{oo'}_{fix}$, before it intersects the post-shock PMC curve, PMC'. For all $Q \leq Q^{oo'}_{fix}$, $PMR(Q) = P^{w,oo}_{fix} > PMC'$. For any output larger than $Q^{oo'}_{fix}$, $PMR(Q) < PMC'$. Therefore, the processors produce $Q^{oo'}_{fix} > Q^{oo'}$ and charge the ceiling price, $P^{w,oo}_{fix}$. No shortage is created.

Both CS and PS increase relative to the flexible-price case, with the gain to each group from the fixed price indicated by the shaded areas in figure 7. Specifically, CS under fixed price equals area $BDP^{w,oo}$ which is strictly larger than CS under a flexible price (i.e., area $BCP^{w,oo}_{flex}$). The incremental CS under a fixed price is shaded light pink. Similarly, we find the incremental PS equal area shaded light gray.

In case 2, $P^{w,oo}_{fix}$ intersects the post-shock PMC curve ($PMC^{'}$), 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 $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$ in figure 7.

Given the shortage, the market could clear in various ways. For example, product could be allocated based on queues or waiting lines, 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, the reality seemed to be that available products were allocated randomly based on when shelves were restocked and consumers happened to arrive at stores.

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

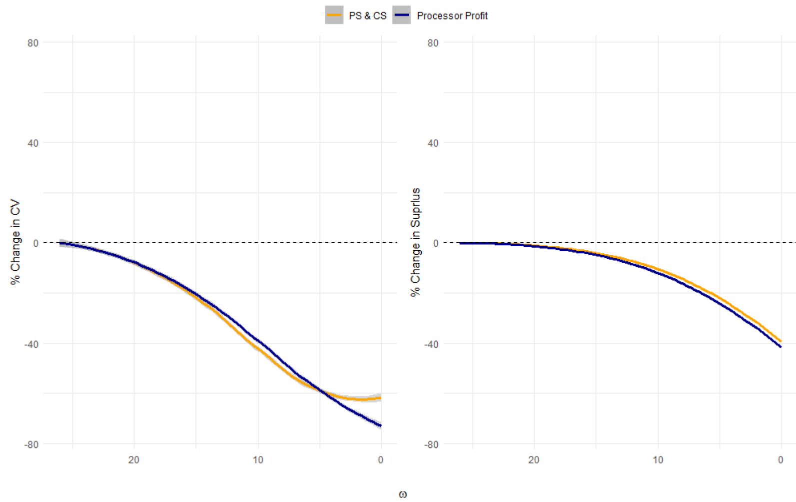
$$\frac{Q_{fix}^{s,oo'}}{Q_{fix}^{d,oo'}} \int_{0}^{Q_{fix}^{d,oo'}} D'(Q) - P^{w,oo} \, dQ \tag{16}$$

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

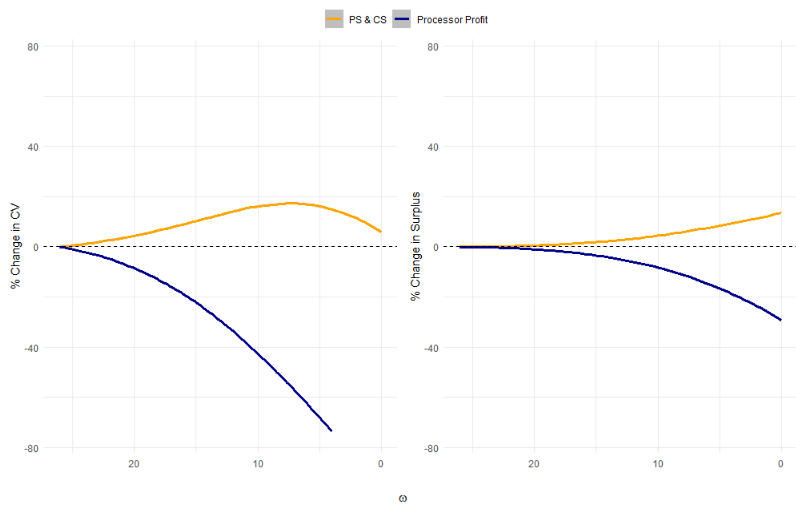
As noted, anti-price gouging laws typically allow some increase in prices post-shock. We, hence, incorporate a continuum of price flexibility from the pre-shock level, $P^{w,oo}$ by setting wholesale price $\bar{P}^{w,oo} = P^{w,oo}(1+\omega)$. Smaller values of ω denote a tighter price ceiling. For sufficiently large values of omega, the price ceiling will not bind.

The base parameters in our simulation model illustrate case 1. We present simulation results in figure 8 for $\omega \in [0, 0.25]$, where $\omega = 0.25$ allows sufficient price flexibility that the ceiling does not bind in our model, while $\omega = 0$ represents no flexibility and price fixed at the pre-shock level. Results for perfect competition are presented in panel (a), intermediate market power in panel (b), and high market power in panel (c). Even though binding price ceilings may increase industry output under market power, thus boosting mean CS and PS, the increase in variance of CS and PS is typically even larger, resulting in a rising CV. The marginal effect of a price ceiling on both mean CS and PS and CV increases as market power increases—illustrated by comparing the efficiency impacts of panels (b) and (c). Thus, in the presence of market power and market conditions that fit case 1, fixing prices downstream from the farm benefits both consumers and farmers in terms of average market surplus, but it does not reduce the variability of market returns.

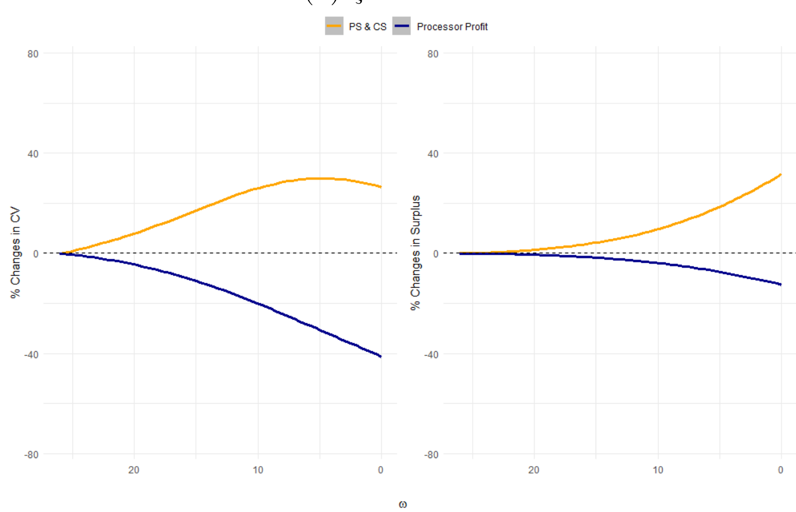
Under perfect competition (panel (a)), a binding price ceiling limits the relative volatility experienced by processors, consumers, and producers, but leads to welfare losses for both producers and consumers due to the shortage that necessarily occurs in the competitive case and restricting both farm production and consumption below the surplus-maximizing levels (see more discussion in Appendix A). For example, allowing prices to increase by no more than 10%, decreases the CV of CS and PS by approximately 35%, but on average CS and PS are lower by about 15%.



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



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



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

Figure 8: Increasing Resilience by Fixing Prices

5 Discussion and Conclusion

In this study, we use a flexible oligopoly-oligopsony model to evaluation the resilience and welfare impacts of five major policy alternatives under extreme events along the agricultural supply chain. We show that each policy option merits some gains to a more resilient agricultural supply chain, but are context specific and yield significant efficiency tradeoffs.

Importantly, these results should not be interpreted as policy prescriptions. While many of these policy changes show larger resilience improvements than efficiency losses, this analysis is conducted assuming that an extreme event occurs – instigating simultaneous shifts int the food supply chain. In reality, extreme events occur under with a likelihood, and optimal resilient-promoting strategies must weigh the year-to-year preparatory costs with the probabilistic expectation of an extreme event.

Supply chain resilience has become a clear focus for food supply chain stakeholders. This analysis provides an theoretical framework for the assessment of these policies and complements the large body of qualitative work on food supply chain resilience. However, this work remains a broad perspective of an emerging field for food and agricultural economists. This framework serves as a building block for future work in this arena as new policies unfold and supply chain deficiencies realized.

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A More Discussion on Price Gouging

When there is limited market power on the seller side, the fixed price, $P^{w,oo}$, may easily intersect the new PMC curve before Q^{oo}. As the figure 9 shows, the processor would produce at $Q^{s,oo'}_{fix}$. The welfare impacts under random allocation of limited supply is discussed in the main context. The supply shortage equals $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$.

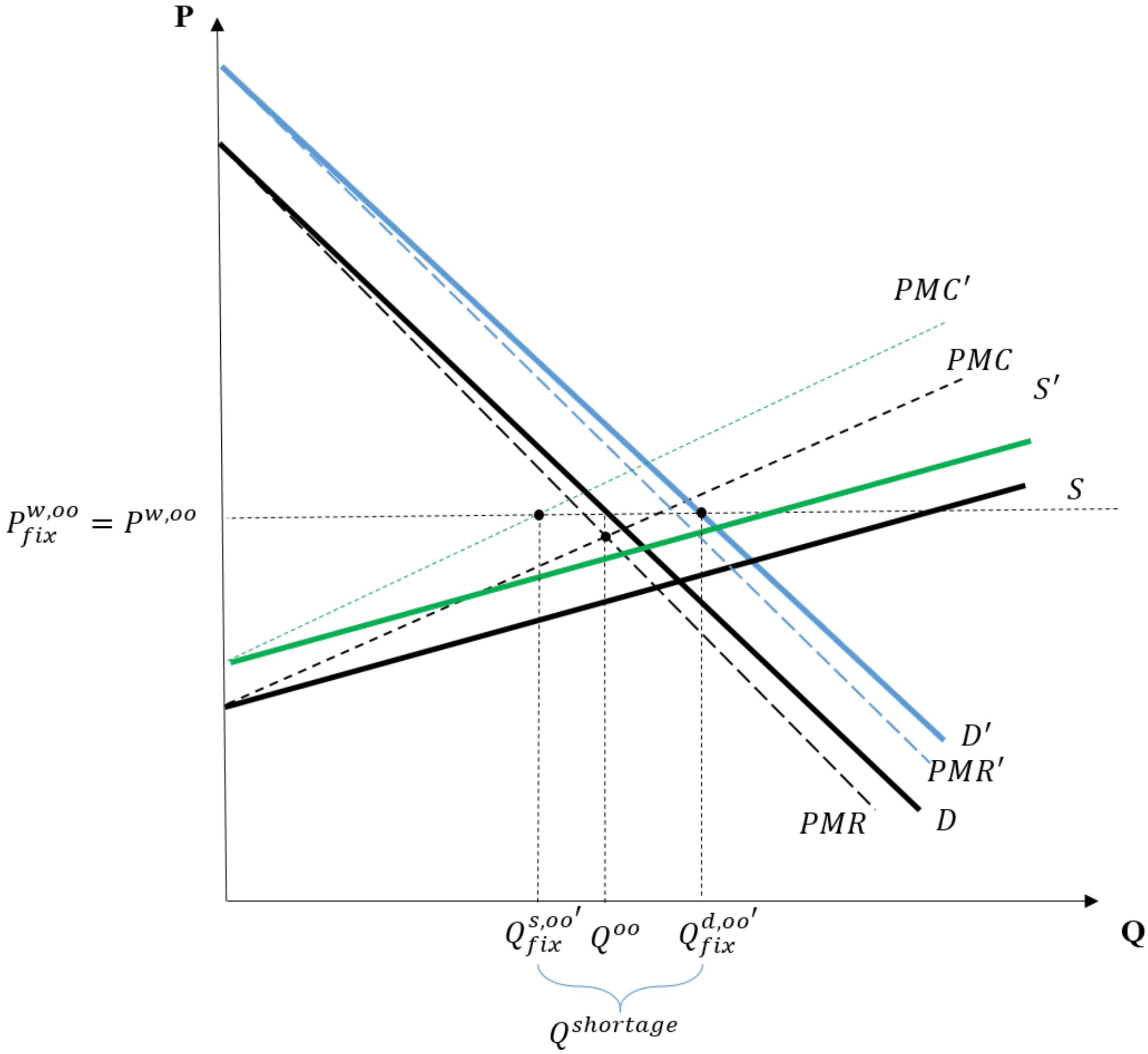

Figure 9: Fixing the Retail Price under Limited Seller Power

The price ceiling could also be imposed on the farm price. If setting $P^{f,oo}$ as the price ceiling for the farm price, $P^{f,oo}$ is effectively the PMC for purchasing farm outputs for processors, only $Q^{s,oo'}_{fix}$ would be supplied by farmers post-shock and is strictly smaller than Q^{oo}. At this fixed farm price, processors are willing to produce at where $P^{f,oo}$ meets the PMR curve, $Q^{d,oo'}_{fix}$. Given the farm supply of $Q^{s,oo'}_{fix}$, the shortage of supply is $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$. Under randomly allocation, of course, rent would not be fully dissipated as discussed in the main context.

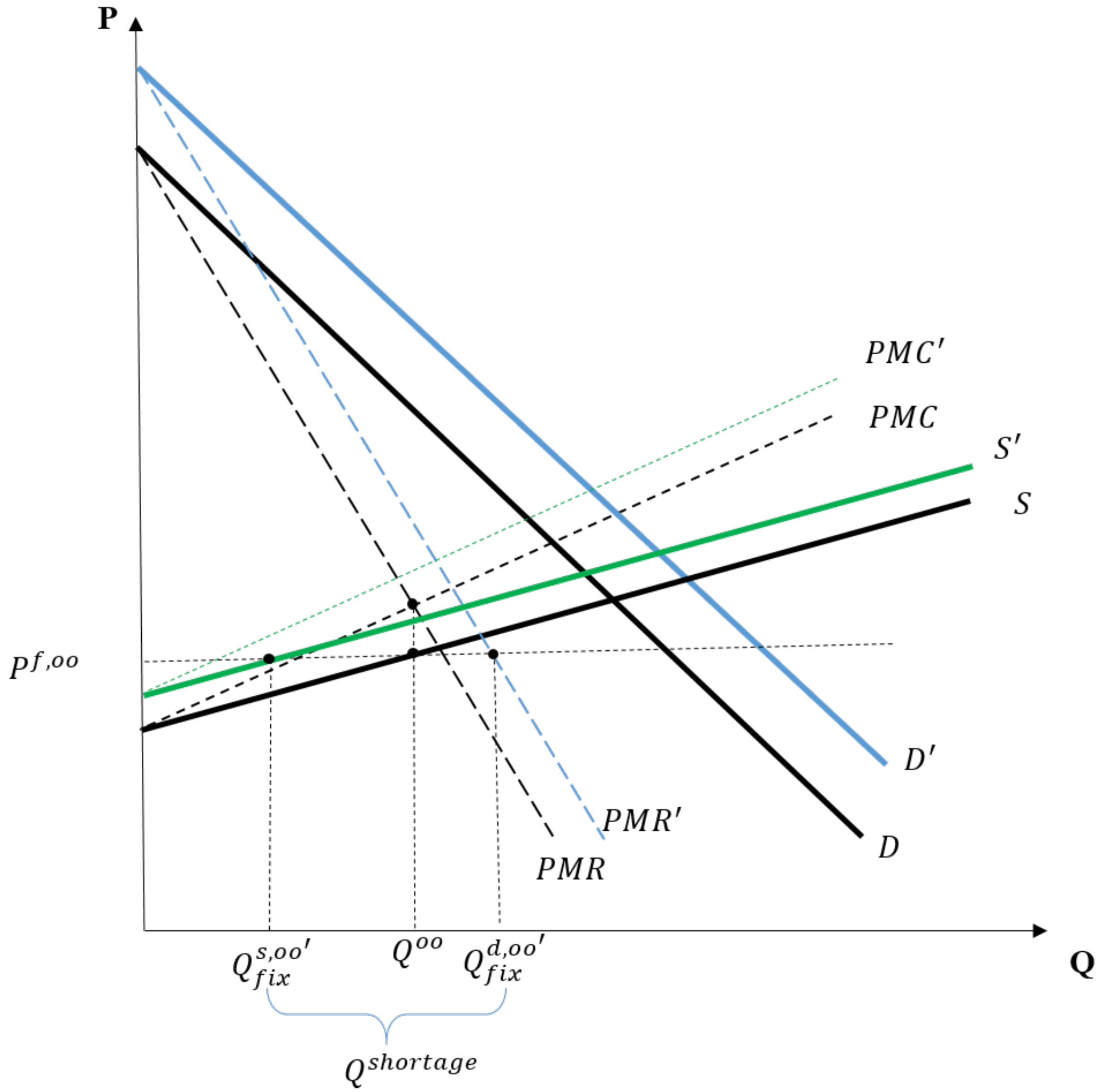

Figure 10: Fixing the Farm Price

Finally, the effect of wholesale price stickiness under no seller power is illustrated in figure 11. 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^d_{fix} prior to the shocks. Post the shocks, the price is fixed at P_{fix}. This price meets the new PMC curve at Q^s_{fix} which is strictly smaller than Q_{flex}. The shortage of supply is $Q^d_{fix} - Q^s_{fix}$.

B Relative Variance

The changes in CV for CS and PS and for processor profits can be better understood via showing the mathematics. We start with CS. Recall that CS equals $\frac{(a-P^{w,oo})Q^{oo}}{2} = \frac{\alpha}{2}(Q^{oo})^2$ where

$$Q^{oo} = \frac{a(1-\frac{\xi}{\eta}) - b(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta(1+\frac{\theta}{\epsilon})}. \tag{17}$$

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

$$Q^{oo\prime} = \frac{a'(1-\frac{\xi}{\eta}) - b'(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta(1+\frac{\theta}{\epsilon})}\frac{N'}{N}. \tag{18}$$

The corresponding CS, CS', can be computed as $\frac{\alpha}{2}(Q^{oo\prime})^2$

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

$$\frac{\sqrt{\sum_{i=1}^{I}(CS_i' - \bar{CS})^2\delta_i}}{\bar{CS}} = \sqrt{\sum_{i=1}^{I}(\frac{CS_i'}{\bar{CS}} - 1)^2\delta_i}, \tag{19}$$

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

Intuitively, the larger deviation of CS_i' relative to CS the larger standard deviation relative to the mean of CS. Therefore, CV increases in the relative magnitude of the CS pre and post shocks. Trend in CV and trend in mean surplus hence agree in the direction. Specifically,CV increases in $\frac{CS'}{CS}$, which is proportional to $\frac{Q^{oo\prime}}{Q^{oo}}$, if $\frac{CS'}{CS} > 1$. If $\frac{CS'}{CS} < 1$, CV decreases in $\frac{CS'}{CS}$.

Taking $\frac{CS'}{CS} > 1$ or $\frac{Q^{oo\prime}}{Q^{oo}} > 1$ for instance, which is typically the case in our baseline simulations, CV increases in the ratio of:

$$R = \frac{a'(1-\frac{\xi}{\eta}) - b'(1+\frac{\theta}{\epsilon}) - c^w}{a(1-\frac{\xi}{\eta}) - b(1+\frac{\theta}{\epsilon}) - c^w}. \tag{20}$$

It is easy to show that R decreases in ξ if $a' > a$ (i.e., a positive demand shock) and $a'b > ab'$ which holds under our baseline setup. This ratio also increases in θ if $b' > b$ (i.e., a negative production shock) and $a'b > ab'$ which also hold under our baseline setup. Similarly, given that PS equals $\frac{\beta}{2}(Q^{oo})^2$, one can show that CV of PS is determined by $\frac{PS'}{PS}$ which is also proportional to $\frac{Q^{oo\prime}}{Q^{oo}}$. Therefore, the CV of CS and PS always overlap. For the same reason, percentage changes in CS and PS, or $\frac{CS'-CS}{CS}$ and $\frac{PS'-PS}{PS}$, agree in magnitude.

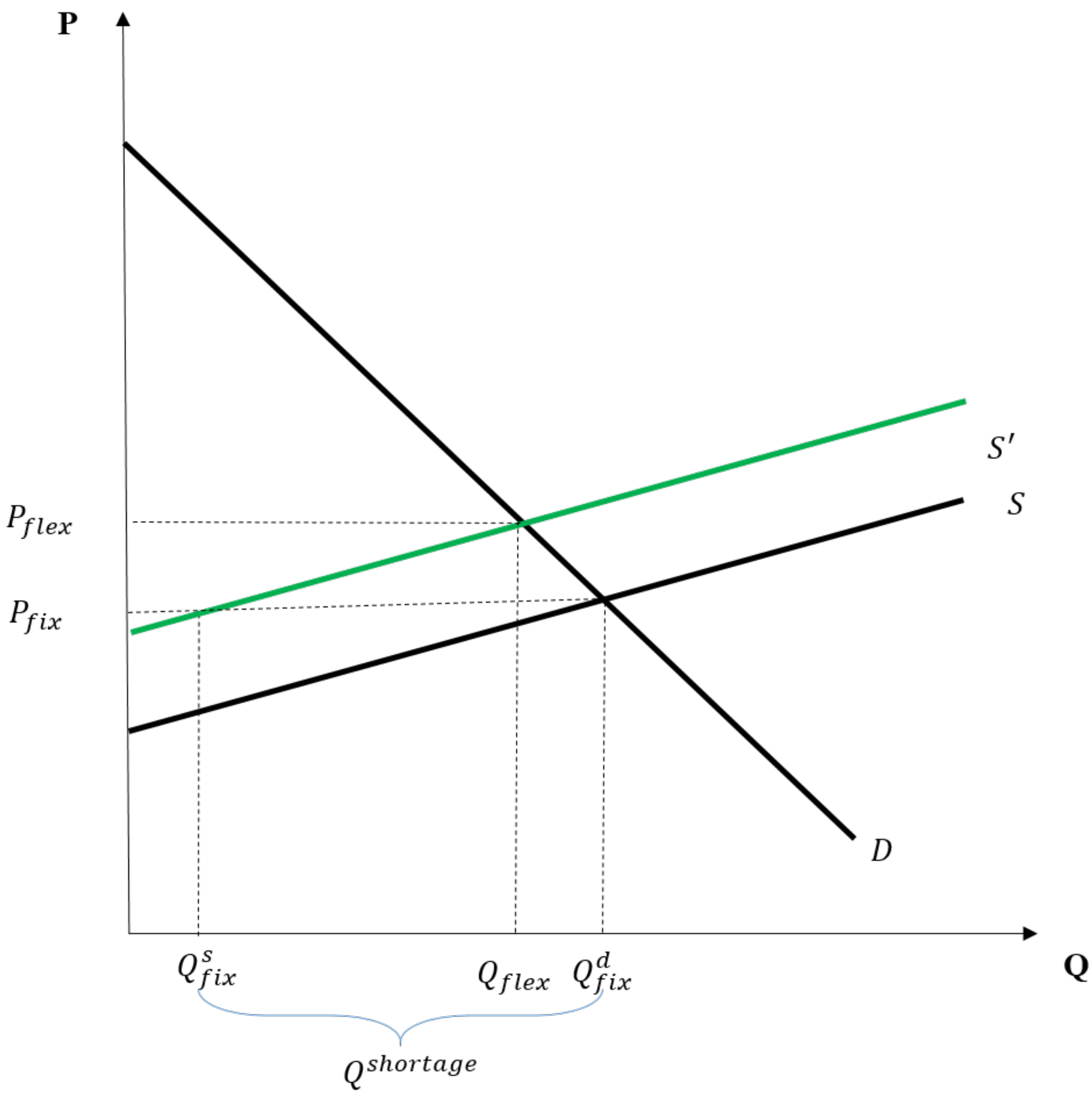

Figure 11: Fixing the Retail Price under No Seller Power