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RESEARCH ARTICLE

Measuring and Explaining State-Level Heterogeneity in Beef Packing Resilience During the COVID-19 Disruption

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Abstract

The USDA's resilience strategy of subsidizing small meat-packer entry has prompted studies on plant size, market structure, and resilience, each study employing a different conception of resilience. None accounts for the duration and speed of slaughter downturns and recoveries. We account for these factors by developing metrics across 35 U.S. states and estimating how the metrics vary with plant size, labor conditions, and COVID-19 policies. We find medium-sized plants enhanced resilience during COVID-19, raising questions about the USDA's narrow focus on smaller plants. This highlights the need for more nuanced strategies to strengthen the resilience of the beef processing sector.

Keywords: beef-packing plant size; resilience metrics; COVID-19 pandemic

JEL classifications: D10; L50; Q18

1. Introduction

The global outbreak of the COVID-19 pandemic unleashed challenges of historic proportions across food systems, the beef-packing industry being no exception. With an exponential increase in COVID-19 cases, more rapidly among beef-packing plant workers in the United States (Krumel and Goodrich, 2023; Saitone et al., 2022), some meat processing plants were forced to shut down temporarily or operate under reduced capacity, resulting in an unprecedented disruption in the U. S. beef supply chain.

COVID-19, which became a pandemic by late February and early March of 2020, caused the first beef-packing plant shutdown in the United States (JBS USA in Souderton) on March 31. By mid-June, 14 plants had shut down or operated at reduced capacity, with total shutdown or reduced operation days reaching as high as 21 days for some plants (McCarthy and Danley, 2020). Since these were large plants with a slaughter capacity of 3,000-7,000 head per day, the disruption in cattle slaughter volume for these high-capacity packing plants led to a significant decline in beef production between April and mid-June 2020. Weekly federally inspected steer and heifer slaughter bottomed out at 356 million pounds during the week ending May 2, 35% lower than the peak volume five weeks earlier and 34% less than the 2019 volume for the same week (Fig 1). Beef-packing plant utilization declined to almost 45% by the middle of May (Cowley, 2020).

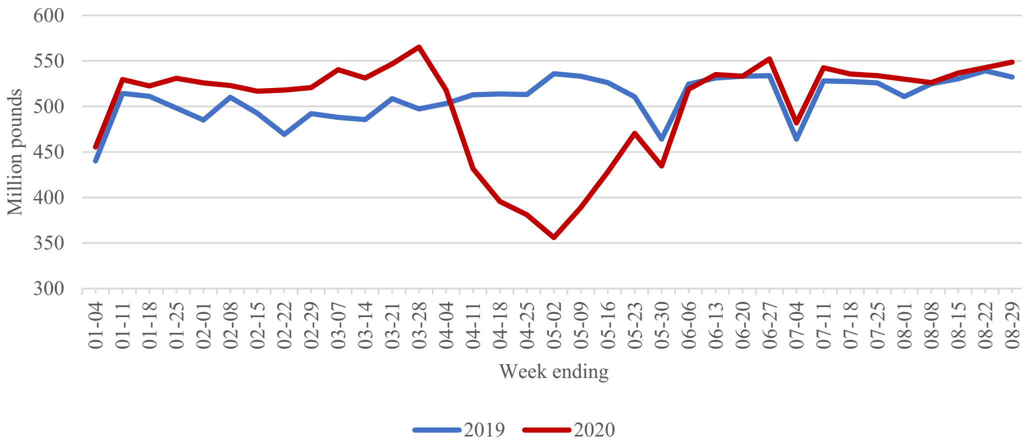

Figure 1. Weekly federally inspected cattle slaughter. Data source: USDA NASS, 2024.

The COVID-19 pandemic and its subsequent disruption of the beef supply chain prompted the government to take initiatives to make it more resilient, considering the possibility of future shocks like COVID-19 (The White House, 2021). Since the packing plants affected during the COVID-19 pandemic were primarily the large ones owned by the big four beef processors (Tyson, Cargill, JBS, and National Beef), leading to severe slaughter bottlenecks, the dominant policy prescription that emerged after the pandemic for increasing the resiliency of the beef supply chain was to reduce reliance on large plants for slaughter by expanding the processing capacity of more geographically dispersed small and medium-sized plants and, in so doing, reduce COVID-19 transmission among plant workers (MAC, 2021; CFRA, 2020, Saitone et al., 2022). In line with this policy, the USDA announced a $4 billion investment in strengthening the food supply chain, including a $500 million grant for expanding the processing capacity of smaller and local food processing plants (USDA Press Release, 2021).

The USDA's inherent assumption that a less concentrated industry, in terms of slaughter plant capacity, would be more resilient to COVID-19-type shocks prompted two strands of studies: retrospective studies on plant size and resilience, and prospective studies on the effect of changes in market structure and resilience. The retrospective ones are nonstructural analysis, using econometric models to directly estimate the relationship between various slaughter disruptions and plant capacity during the pandemic, while remaining agnostic to the market effects of these disruptions (Bina et al., 2022; Cooper et al., 2023; Dhoubhadel et al., 2024). The prospective ones are structural analysis, utilizing theoretical industrial organization models that assess whether additional plants or reallocation of slaughter between existing small and large plants under a shock affect market competition, output and prices, and resilience (Hadachek et al., 2023, Ma and Lusk, 2021), and under what conditions additional capacity in the industry ensures its robustness under a pandemic-like shock (Azzam, 2023). Although the USDA left unclear what "resilience" meant when it launched the initiative, each study has its own conception of resilience. Resilience in this literature, which we review in a separate section below, is either inferred from the decline in slaughter relative to preshock levels (Bina et al., 2022; Cooper et al., 2023), considered as a binary outcome in Dhoubhadel et al. (2024), defined as a static equilibrium in which beef production is robust to a change in capacity (Azzam, 2023), or considered as a static equilibrium in which additional plants minimize social welfare losses (Hadachek et al., 2023; Ma and Lusk, 2021).

The fact that the studies conceptualize resilience differently is unsurprising, as there is no universal concept or metric of resilience. However, as Azzam et al. (2023) demonstrate, the fluctuations in beef production during COVID-19 – including declines and recoveries (Fig 1) and the metrics to measure resilience to such disrruption – align closely with some of the metrics used in regional economics to assess the resilience of regional economies during recessions, which similarly account for downturns and recoveries of varying durations and speeds (Han and Goetz, 2019). Accounting for downturns, subsequent recoveries, their duration, and speed subsumes resilience as a dynamic concept (Holling, 1996) than the static concepts used so far by both structural and nonstructural studies of beef-packing resilience to the pandemic.

However, accounting for downturns, recoveries, their duration and speed in a structural model of beef-packing resilience and plant size is a tall order, as this would require a time-dependent constrained profit-optimization model that traces the path between peaks and troughs of industry slaughter during the pandemic, apart from the rich data required to estimate or calibrate the model. That leaves the nonstructural approach as the less onerous option for exploring the relationship between plant capacity and a resilience measure that accounts for the observed drops and rebounds in cattle slaughter, as well as their speed and duration.

In this light, our paper contributes to the retrospective nonstructural literature on beef-packing resilience and plant size by building on Azzam et al.'s (2023) work on comparative U.S. and European Union meat processing resilience to COVID-19. Specifically, we leverage the heterogeneity in cattle slaughter across U.S. beef-producing states to (a) compute resilience metrics for each state during the pandemic and (b) explore the relationship between these metrics and state-specific reliance on different plant sizes, labor conditions, and COVID-19-related policy variables – the three factors Azzam et al. (2023) hypothesized as key drivers of resilience and explicitly tested by Dhoubhadel et al. (2024) in their survey-based study of smaller plant resilience.

The following section provides an overview of the methods and findings of the beef-packing resilience literature mentioned earlier. Section 3 elaborates on the conceptual framework underlying the resilience metrics. Section 4 calculates these metrics, using Nebraska as an illustrative example, and provides a qualitative discussion of state-level resilience rankings. Section 5 presents the findings from a regression analysis employing the weighted Poisson Pseudo-Maximum Likelihood method. Section 6 contains the summary, conclusions, policy implications, and limitations.

2. Overview of the Literature

Using weekly regional fed-cattle slaughter during the early period of COVID-19, Bina et al. (2022) evaluate the structure and performance of the beef processing industry during the early stages of the COVID-19 pandemic. They measure performance by the 2020 and 2019 slaughter ratios and structure by the respective capacity shares from plants with 2,000-4,999 and 5,000 or more head/day slaughtered. The capacity shares are interacted with temporal dummy variables at 4-week intervals. The authors find that a higher reliance on large plants affected performance negatively only during certain time intervals, concluding that the industry exhibited "some degree of internal resiliency" (p. 7). While the authors do not offer a specific metric for resiliency, they infer its degree from the relative number of time intervals with statistically insignificant declines in cattle slaughter.

Cooper et al. (2023) use daily plant-level data from the 33 largest cattle plants from April 6, 2020, through January 18, 2022. The authors construct two measures of performance: daily plant underutilization (cattle slaughter as a percent of capacity) and daily plant underperformance (the difference between actual cattle slaughter and regular slaughter as a percent of routine slaughter). Results from a logit fractional regression of the two performance measures on plant capacity, the S&P 500 index as a proxy for demand, the county-level 7-day average of COVID-19 cases, and plant age in years indicate that while industry performance was weak during the pandemic's initial phase, it recovered afterward. They conclude that additional smaller plants could have mitigated reliance on the larger plants early, but not later in the pandemic. Like Bina et al. (2022), the authors interpret their results as indicative of the industry's resilience during the pandemic but offer no specific metric to measure it.

Dhoubhadel et al. (2024) use survey data from 289 plants with daily slaughter capacities ranging from 1 to 5200 head. The authors define a plant as resilient if it maintained or increased slaughter during COVID-19, and not resilient if it reduced slaughter during the same period. They estimate a logit model in which the probability of plant resilience is a function of its capacity, labor conditions (proxied by wages and whether a plant is located in a state with the Right-to-Work law), and COVID-19 policy (proxied by whether a plant is located in a state with a mask mandate). Their findings suggest that the smaller the plant, the higher the resilience. They report that none of the smaller plants closed during the pandemic, although some reduced their volume, many maintained or even increased slaughter during COVID-19. This finding contrasts with the number of shutdowns of larger plants, as reported by McCarthy and Danley (2020), suggesting that smaller plants could be a more resilient outlet for market-ready cattle. What differentiates Dhoubhadel et al.'s study from the other studies is that they define resilience, correlate it with industry and policy variables, and focus on smaller plants.

Azzam (2023) employs the comparative statics of a dominant-firm competitive fringe theoretical model to analyze the resilience of the U.S. meatpacking industry. Defining resilience as an industry equilibrium in which beef production continues at its normal level, he finds resilience achievable if the dominant firm, represented by larger processors, behaves competitively and shares cattle slaughter equally with the competitive fringe, the smaller packing plants.

Ma and Lusk (2021) employ a Cournot model calibrated to 2019 beef-packing data to examine how industry structure impacts resilience. They simulate 1,000 plant shutdown scenarios, comparing total surplus under two market structures – one with only small plants and one with only large plants. Resilience is measured by average surplus across simulations. They conclude that despite spreading the risk of shutdown, a less concentrated industry with small plants is not necessarily more resilient due to higher cost inefficiencies.

Hadachek et al. (2023) build on Ma and Lusk (2021) by adopting a conjectural elasticity model to capture varying industry conduct. They simulate the impact of symmetric firm entry on welfare, considering competition and cost efficiency under joint shocks at different supply chain levels. Measuring resilience by the coefficient of variation in welfare, they find that resilience depends on how much entry reduces the market power of incumbent beef packers.

The key takeaways from this literature are as follows: Regional data show that reliance on large plants reduced resilience during certain periods of the pandemic. Survey data indicate that most small packers withstood the pandemic, with smaller plants proving even more resilient. However, USDA plant-level data on federally inspected slaughter suggest that small plants only helped buffer disruptions in the early stages of the pandemic. Regarding processor entry and market structure, the literature suggests that a less concentrated industry with more small plants is not necessarily more resilient, since this depends on how new entrants affect the market power of large incumbent packers. Importantly, as noted earlier, none of the existing studies considered the duration and speed of cattle slaughter declines and recoveries as measures of resilience. We address these elements in the next section.

3. Resilience Metrics: Conceptual Framework

Figure 2 illustrates the simple case of a single drop and a rebound of cattle slaughter (Q_t) due to the pandemic shock relative to expected slaughter ($Q_{t\ exp}$) in normal times during the same period. The solid and dashed lines, respectively, trace actual and expected slaughter. When shocked at time t_1, slaughter drops from Q_1 to Q_2 at time t_2 and rebounds to Q_3 at time t_3. The relative output in each period, R_t, is defined as $Q_t/Q_{t\ exp}$, with $R_t < 1$ for $t = t_1$, t_2, and t_3. So, R_1, R_2, R_3 represent relative output in time t_1, t_2, t_3, respectively. In cases where actual slaughter exceeds expected

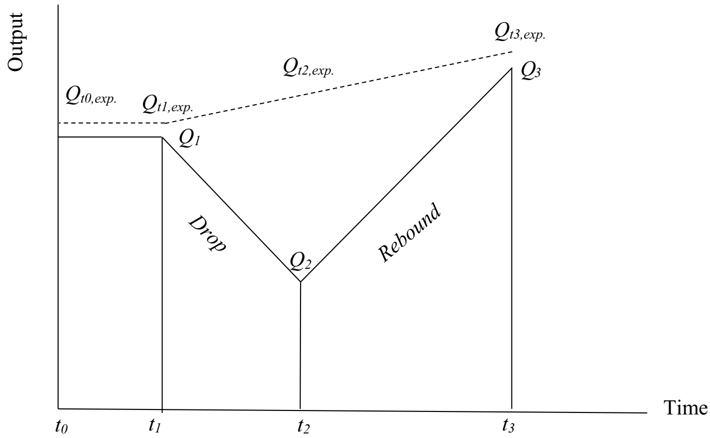

Figure 2. Drop and rebound in cattle slaughter during the pandemic relative to expected slaughter in normal times. Source: Azzam et al., (2023).

slaughter at t_1 or t_3, $R_t > 1$. Intuitively, a beef-packing plant that experiences a smaller drop and a more substantial rebound in cattle slaughter is more resilient.

Following Azzam et al. (2023), the four resilience metrics we consider are ordered by the number of dimensions they incorporate, including relative size drops and rebounds, duration, and speed. The first metric, using Figure 2 as a reference, is

$$R^{Magnitude} = (R_3 - R_2)/(R_1 - R_2) \tag{1}$$

It measures the magnitude of recovery relative to the magnitude of the drop, represented by the ratio of the difference in relative slaughter levels during the recovery and drop phases. The larger the magnitude of the recovery phase relative to the drop phase, the higher the resilience.

However, the metric does not account for the time duration of the drop and rebound.

The second metric accounts for the magnitude of the drop, rebound, and duration:

$$R^{Speed} = s_r/s_d \tag{2}$$

where $s_r = (R_3 - R_2)/(t_3 - t_2)$ and $s_d = (R_1 - R_2)/(t_2 - t_1)$ are the speed of recovery and drop. Resilience is high when the speed of the recovery phase is higher than that of the drop phase, and vice versa.

Although $\mathcal{R}^{speed}$ accounts for the speed, it doesn't account for the relative magnitudes of drop and recovery, implying that the value of $\mathcal{R}^{speed}$ can be higher even if the magnitude of the drop is larger than that of the recovery. The metric that remedies the deficiency is:

$$R^{Momentum} = s_r w_r / s_d w_d \tag{3}$$

where $w_r = (R_3 - R_2)/R_2$ and $w_d = (R_1 - R_2)/R_1$ are the relative magnitudes in the recovery and drop phases. $\mathcal{R}^{Momentum}$ captures the effect of speed and relative magnitude. In this case, resilience could be higher even if the recovery speed is low, provided the relative magnitude of recovery is high, and vice versa.

The fourth metric is:

$$R^{Force} = (s_r - s_d)w_r/(s_d - s_0)w_d \tag{4}$$

where $s_0 = (R_1 - R_0)/(t_1 - t_0)$. As shown in Figure 2, s_0 is assumed to be zero before the shock at t_1. Resilience is higher when the change in speed or the relative magnitude of the recovery phase is greater than the drop phase.

To extend the above framework to multiple drops and rebounds, Azzam et al. (2023) construct the following phase-weighted resilience index, where each phase represents a drop and its associated rebound:

$$RES^i = \sum_c t^c R^i / t \tag{5}$$

for $i =$ *Magnitude, Speed, Momentum, and Force,* as defined by equations (1)-(4). The time length from the beginning of the drop until the end of the rebound is indicated by t^c, and t is the total number of months in the study period. In all cases, resilience metrics imply that the detrimental effect of a drop in output is more than offset by the beneficial impact of recovery.

4. Resilience Metrics Computation

The first step in computing the resilience metrics is to forecast each state's normal slaughter (without a pandemic) between March and December 2020, that is, the expected slaughter ($Q_{t\ exp}$) in normal times, as illustrated in Figure 2. A common approach in the literature is representing "normal" by slaughter in 2019 or by an average over a few pre-pandemic years (Bina et al., 2022; Cooper et al., 2023). While the approach is simple to implement, applying it to states would not account for the heterogeneity in historical cattle slaughter levels, trends, and seasonality, as some states have gained and others have lost cattle market share over the years, not just in the year or a few years before the pandemic.

For each of the 35 States, we used the Holt-Winters forecasting method (Hyndman and Athanasopoulos, 2021) to forecast cattle slaughter between March and December 2020. The method accounts for the level, trend, and seasonality of data typical of cattle slaughter between January 1983 and February 2020 for each State (USDA NASS, 2024) to forecast what would have been expected cattle slaughter in 2020.

Briefly, the forecasting method works as follows: Given the historical monthly time series of a state's cattle slaughter between January 1983 and February 2020, Q_t, for $t = 1. \ldots, T$, where T is *February* 2020, and $h =$ *March, April, ….., December* 2020, the one-step ahead forecast is

$$\hat{Q}_{t+h|t} = L_t + hb_t + s_{t+h-m(k+1)}$$

where, $L_t = \alpha(Q_t - s_{t-m}) + (1-\alpha)(L_{t-1} + b_{t-1})$ is the level of cattle slaughter at time t, $b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ is the trend, and $s_t = \gamma(Q_t - L_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$ is the season, α, β, and γ are smoothing parameters, and k is the integer part of $(h-1)/m$, where m is the number of periods per year (Hyndman and Athanasopoulos, 2018, Section 8.3). Figure 3 illustrates the method's performance using Nebraska's monthly cattle slaughter and the SAS Proc Forecast software (SAS Institute Inc., 2014). It shows the state's actual and predicted cattle slaughter up to February 2020, followed by the expected slaughter ($Q_{t\ exp}$) from March to December 2020 had the pandemic not occurred, alongside the actual slaughter during the same period.

The second step is calculating R_t (the actual and expected slaughter ratio) and the time between drop and recovery. Then, we compute the four resilience metrics based on equations 1- 5 in two sets for each of the 35 states. Set 1, ($\mathcal{RES}^i_{1st\ phase}$), covers for each state the first drop and rebound starting in March (covering the first peak-trough-peak or trough-peak-trough period). Set 2, ($\mathcal{RES}^i_{all\ phases}$), covers the multiple phases during the March-December 2020 period.

We give an example using Nebraska data to illustrate how we compute state-level resilience metrics. Figure 4, excerpted from Figure 3, contrasts actual versus normal (expected without COVID-19) slaughter in the state. The data for plotting the figure and constructing the resilience metrics for the state are in Table 1. The first three columns of the table list the months, actual or

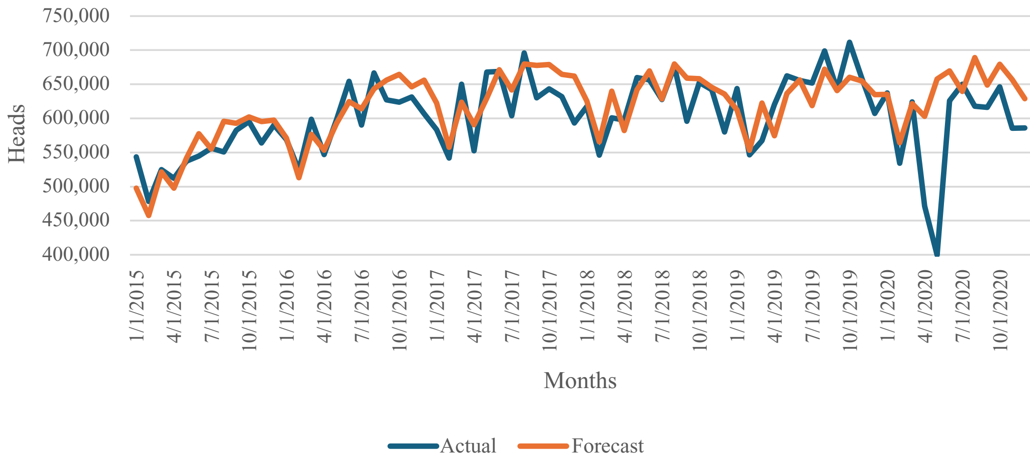

Figure 3. Nebraska actual and predicted cattle slaughter. Note: the forecast for March-December 2020 shows what the cattle slaughter might have been without COVID-19 disruption. Data source for actual cattle slaughter: USDA NASS, 2024.

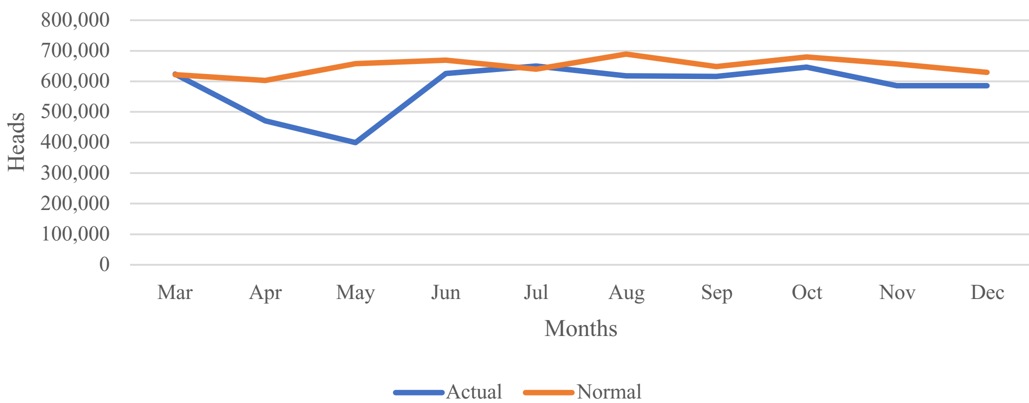

Figure 4. Monthly Nebraska cattle slaughter in 2020 actual vs normal. Data source for actual cattle slaughter: USDA NASS, 2024.

pandemic slaughter, and normal slaughter. Column 4 is the pandemic-to-normal slaughter ratio. Column 5 identifies the trough or peak of a phase. The periods (months) corresponding to the peaks and troughs are in column 6. Columns 7 through 10 show the numerical values of the first four resilience metrics represented by equations 1- 4. The metrics are placed at the end of each phase (peak-trough-peak) in rows 6, 9, and 11. The numerical value of each resilience metric's time-weighted average ($\mathcal{RES}^{i}_{all\ phases}$), represented by equation (5), is in the last row. The higher the numerical value of the metric, the higher the resilience. Column (11) identifies the phases, each consisting of a peak, a trough, and a peak. In the Nebraska case, there are 3 phases.

Figure 5 maps out the four resilience metrics for the 35 states. For each metric, Table 2 lists the five most resilient states, Table 3 lists the five least resilient states, and Table 4 shows the resilience rankings of the top five beef-producing states in 2020 (Texas, Nebraska, Kansas, Colorado, and California) among the 35 states and the top five beef-producing states. The latter rankings are inside the square brackets in Table 4.

The qualitative insights are as follows: None of the top five beef-producing states ranks among the five most resilient. Nebraska, California, and Colorado are among the five least resilient, with their rankings varying depending on the period and the resilience metric used. However, the

Table 1. Resilience index computation for Nebraska using 2020 March-December slaughter data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Month	Q_t (hd)	$Q_{t\ exp}$ (hd)	$R_t = Qt/\ Q_{t\ exp}$	Peak/trough	t	$\mathcal{R}^{Magnitude}$	$\mathcal{R}^{Speed}$	$\mathcal{R}^{Momentum}$	$\mathcal{R}^{Force}$	Phases
(2)	Mar	624,000	621,757	1.004	$R_1 =$ Peak	t_1					
(3)	April	471,200	602,957	0.781							
(4)	May	399,700	657,610	0.608	$R_3 =$ Trough	t_3					
(5)	June	625,700	669,596	0.934							
(6)	July	650,100	639,591	1.016	$R_5 =$ Peak	t_5	1.032	1.032	1.760	3.465	1
(7)	Aug	617,800	689,151	0.896	$R_6 =$ Trough	t_6					
(8)	Sep	616,100	648,708	0.950							
(9)	Oct	646,400	679,429	0.951	$R_7 =$ Peak	t_7	0.458	0.229	0.119	0.236	2
(10)	Nov	585,400	657,014	0.891	$R_8 =$ Trough	t_8					
(11)	Dec	585,800	629,009	0.931	$R_9 =$ Peak	t_9	0.667	0.667	0.476	0.817	3
(12)							$\mathcal{RES}^{Magnitude}_{all\ phases}$	$\mathcal{RES}^{Speed}_{all\ phases}$	$\mathcal{RES}^{Momentum}_{all\ phases}$	$\mathcal{RES}^{Force}_{all\ phases}$	
(13)							0.760	0.683	0.927	1.800	

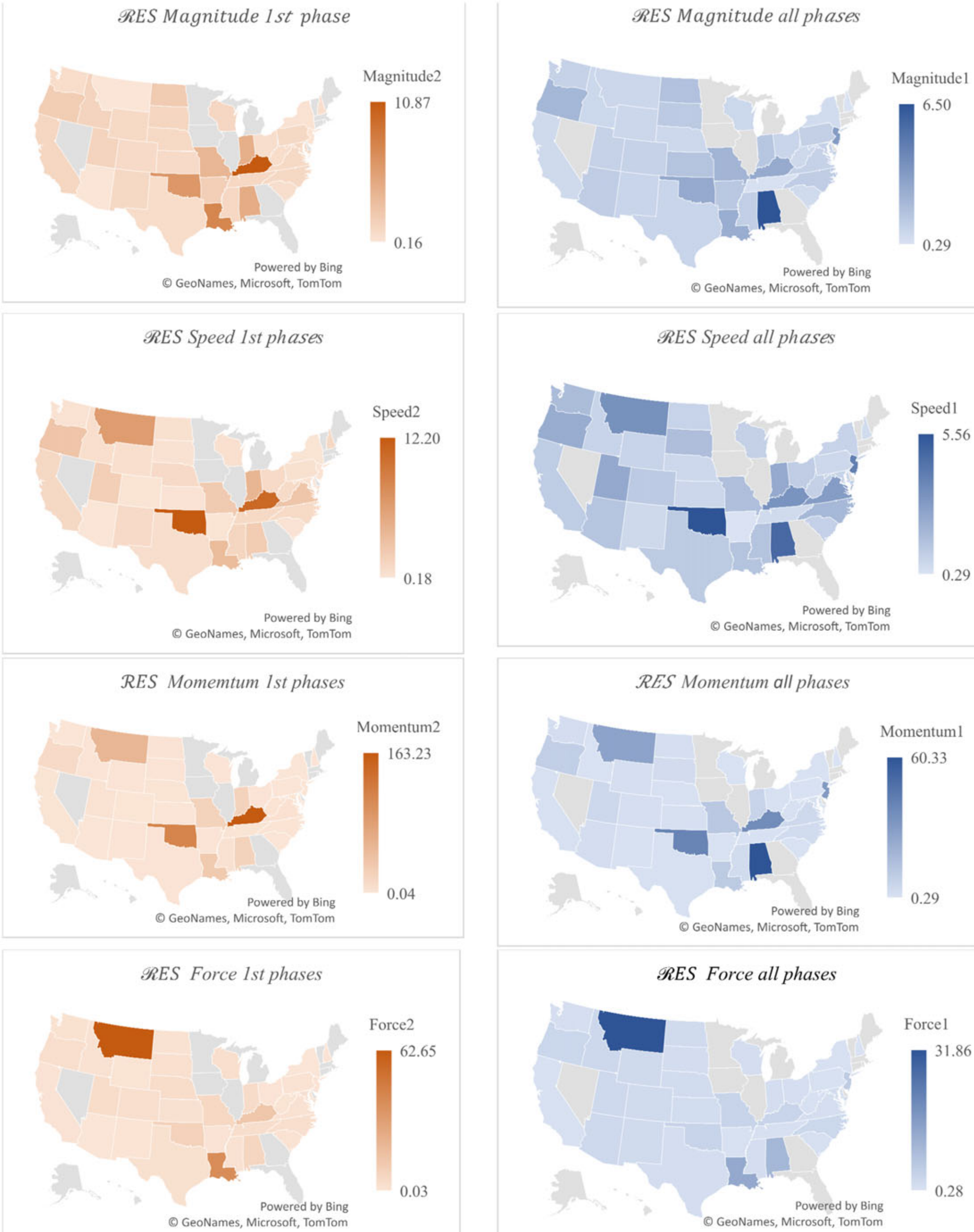

Figure 5. Resilience indices for 35 states. Note: the darker the color shades, the higher the RES values are. The calculated values of resilience metrics are provided in Appendix Tables A1 and A2.

presence of minor beef-slaughter states on both the most resilient list (e.g., Alabama, Kentucky) and the least resilient list (e.g., New Hampshire, Arkansas) suggests that a state's larger share of national beef slaughter does not necessarily correlate with lower resilience. As our econometric model shows below, what matters is a state's reliance on larger plants.

Table 2. Top 5 list of the most resilient states by resilience metrics

	Magnitude		Speed		Momentum		Force	
Rankings	All phases	First phase	All phases	First phase	All phases	First phase	All phases	First phase
1	AL	KY	OK	OK	AL	KY	MT	MT
2	NJ	LA	AL	KY	OK	OK	LA	LA
3	OK	OK	NJ	MT	KY	MT	AL	KY
4	KY	AL	MT	IN	NJ	LA	NJ	OK
5	LA	IN	KY	LA	MT	AL	OK	AL

Table 3. Bottom 5 list of the least resilient states by resilience metrics

	Magnitude		Speed		Momentum		Force	
Rankings	All phases	First phase	All phases	First phase	All phases	First phase	All phases	First phase
31	CA	NH	NE	NY	SC	PA	CA	OH
32	SC	NY	NM	AR	AR	SC	NY	NJ
33	NY	NJ	TN	CO	PA	NY	AR	NH
34	TN	AR	NH	NJ	TN	NJ	WV	NY
35	NH	MT	AR	AZ	NH	AZ	NH	AZ

Table 4. Resilience ranking of the top 5 beef-producing states by resilience metrics

	Magnitude		Speed		Momentum		Force	
States	All phases	First phase	All phases	First phase	All phases	First phase	All phases	First phase
Texas	22 [3]	26 [5]	18 [2]	20 [3]	23 [4]	24 [3]	23 [4]	16 [3]
Nebraska	29 [4]	22 [2]	31 [5]	17 [2]	27 [5]	13 [1]	17 [2]	8 [1]
Kansas	9 [1]	24 [3]	29 [4]	29 [4]	20 [2]	29 [5]	19 [3]	17 [4]
Colorado	19 [2]	25 [4]	17 [1]	33 [5]	19 [1]	27 [4]	16 [1]	13 [2]
California	31 [5]	13 [1]	19 [3]	12 [1]	21 [3]	15 [2]	31 [5]	26 [5]

The figures in [] indicate ranking among the top 5 states.

5. Data and Model

While Bina et al. (2022) use regional weekly data and Cooper et al. (2023) use daily plant-level data, we use monthly state-level data to construct our resilience metrics. The plant-level data used by Cooper et al. (2023) is collected daily but is confidential and restricted. The regional data used by Bina et al. (2022) is available weekly; however, there are only 10 USDA-federally inspected slaughter regions (USDA AMS, 2022), allowing for only 10 cross-sectional resilience metrics. Moreover, subnational COVID-19 policies operated within state borders rather than broader geographical areas, such as the USDA livestock regions.

Due to USDA data disclosure limitations and missing data for some states, our sample is limited to 35 states. With that sample size and monthly observations, we consider our effort an illustrative exercise in constructing and modeling resilience metrics to assess the impact of plant size on the resilience of the U.S. beef-packing industry during COVID. The heterogeneity in

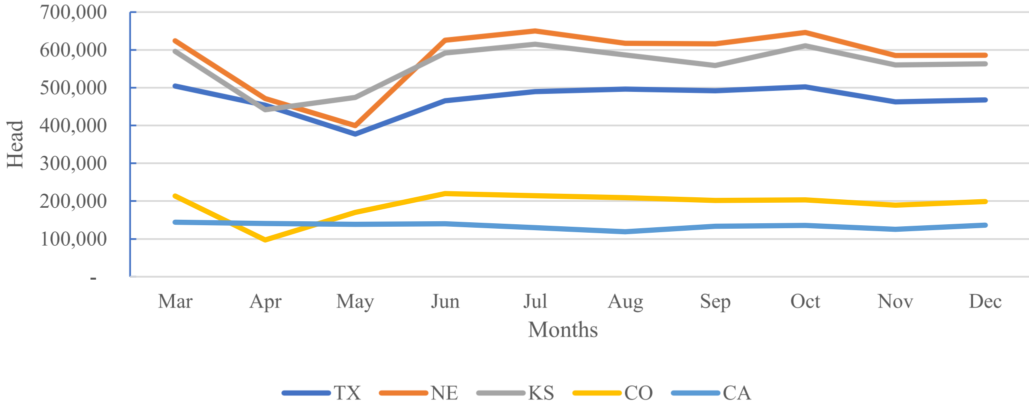

Figure 6. Cattle slaughter of top 5 beef-producing states in March-December 2020. Data source: USDA NASS, 2024.

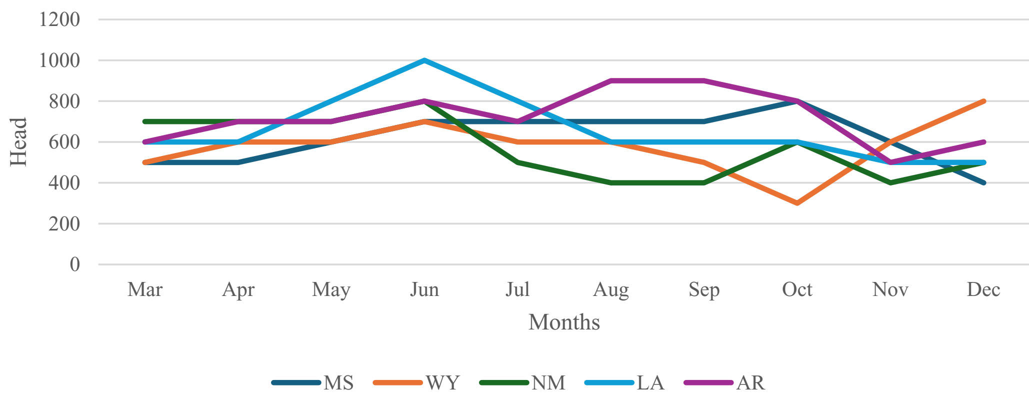

Figure 7. Cattle slaughter of bottom 5 beef-producing states in March-December 2020. Data source: USDA NASS, 2024.

monthly cattle slaughter across these states in 2020, as illustrated in Figures 6 and 7 for the top five and the bottom five beef-producing states, provides the sample variation needed to construct the resilience metrics and test hypotheses about their relationships with plant size and policy variables.

In their comparative study of the United States and the European Union's meat processing resilience to COVID-19, Azzam et al. (2023) hypothesized that differences in the concentration of larger cattle slaughter plants, labor conditions, and public policy regarding COVID-19 were the primary drivers of the resilience differences between the two regions. We adopt the same hypothesis to explain the variation in resilience across U.S. states. Specifically, we estimate the relationship between the four resilience metrics and the three drivers across the 35 states in our sample.

The regression model is:

$$RES^i_{jk} = \beta_{1k} + \beta_{2k}Large_j + \beta_{3k}Medium_j + \beta_{4k}Small_j + \beta_{5k}Difference_j + \beta_{6k}RTW_j + \beta_{7k}Stringency_j + \varepsilon_{ijk} \quad (6)$$

where $\mathcal{R}ES^i_{jk}$ is the i^{th} resilience metric for the j^{th} state, for i = *Magnitude, Speed, Momentum,* and *Force*, $j = 1, \ldots, 35$, and $k =$ *first phase, all phases*, as defined by equation (5). We describe the right-hand-side variables and their respective data sources below. The dependent variable $\mathcal{R}ES^i_{jk}$ was described in the previous subsection.

Large$_j$, *Medium*$_j$, and *Small*$_j$ represent the j^{th} state's proportional reliance on large, medium, and small-sized plants for cattle slaughter. The hypothesis is that a state that relies on larger plants will exhibit less resilience, as such plants enable more disease transmission among workers than smaller plants. Our a priori expectation is that both large and medium-sized plants compromise resilience, with the larger plants having a more detrimental effect on resilience than the medium-sized ones.

We computed the proportions (degree of reliance) for each state based on the Meat, Poultry, and Egg Product Inspection Directory database maintained by the USDA Food Safety and Inspection Services (USDA FSIS, 2024) as follows. The database has five plant size categories and the number of plants in each category. The categories in number of head slaughtered yearly are: 1) less than 10,000 (very small plants), 2) greater than or equal to 10,000 and less than 100,000 (small plants), 3) greater than or 100,000 and less than 1,000,000 (medium plants), 4) greater than 1,000,000 and less than 10,000,000 (large plants), and 5) greater than or equal to 10,000,000 (very large plants). We dropped category five as none of the states in the sample housed a plant of that size.

We proceeded with the remaining categories (1, 2, 3, and 4) as follows. Since FSIS does not report slaughter volume by plant with each category or average slaughter within a category, we estimated the average slaughter volume in each category at the midpoint of the interval, such that the total slaughter volume equals the number of plants in a category multiplied by the midpoint slaughter volume. The total volume in a state is the sum of the respective total volumes of each category. For example, the average slaughter volume for the FSIS category "Greater than or equal to 1,000 and less than 10,000" was calculated as (1000 + 9999)/2 multiplied by the number of plants in that category[1]. We should note that although the estimate of slaughter volume using the midpoint will not necessarily coincide with the actual slaughter volume in each state, what matters in our case is the proportion rather than the total volume in each category as we use the proportions of slaughter volume in a state for those categories to estimate the relationship between proportions of slaughter plant sizes and the resiliency of a state (equation 6).

Next, we summed the slaughter volume in the four categories to calculate the total slaughter volume in a state. We then estimated the proportions of each slaughter volume relative to the total slaughter volume – *Large*$_j$, *Medium*$_j$, *Small*$_j$, and *Very Small*$_j$. Since the four categories sum to one, we dropped *Very Small*$_j$ from the estimation. It should be noted that the greater the proportion of a particular category in a state, the greater the reliance of that state on that plant size category for its beef supply. For example, Figure 8 plots the state-wise proportion of larger plants. It shows that major beef-producing states such as Nebraska, Kansas, and Texas are more reliant on larger plants for their beef supply. To capture this reality, we include the variable *Difference*$_j$, which is simply the difference in the proportions of larger plants and all other plants in a state in the sample. Hence, the greater the value of this variable, the greater is the reliance of a state on larger-sized plants.

We used the binary variable *RTW* as a proxy for labor conditions in a state. We gathered information on states with *RTW* from the National Conference of State Legislatures (NCSL, 2023). The binary variable takes a value of 1 for a state with Right-to-Work (*RTW*) and zero otherwise. While Right-to-Work laws allow employees in the states to work without joining a labor union, they can also affect the collective bargaining ability of workers to demand better labor conditions. The impact of *RTW* laws on resilience is ambiguous. Workers may opt not to work due to the lack of industry requirements to protect them. For example, in Nebraska, an *RTW* state, it is possible that the workers stayed home because the governor at the time refused to implement state-level industry safety requirements, opposed temporary plant shutdowns, and halted reporting COVID-19 cases tied to meatpacking plants (Dineen, 2022). In non-*RTW* states, workers could collectively

[1]The FSIS database had no plants in the "Greater than or equal to 10,000,000" category, so our largest category for average slaughter volume calculation was "Greater than 1,000,000 and less than 10,000,000."

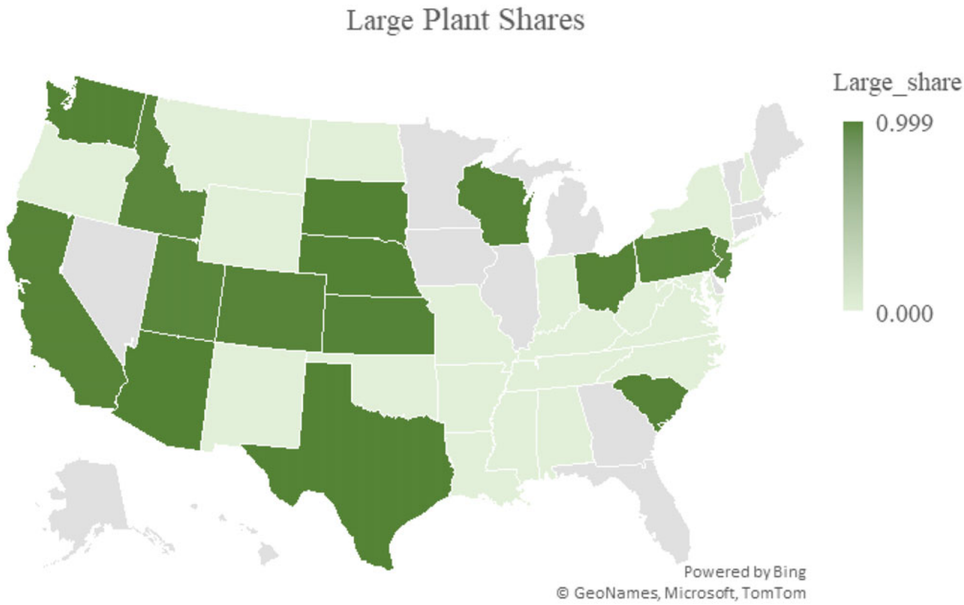

Figure 8. State-wise proportion of beef supply by large plants.

bargain for improved work conditions during the COVID-19 pandemic and return to work relatively quickly.

The variable *Stringency*$_j$ is an index that measures the stringency of the j^{th} state's policy response to COVID-19. The data comes from the Our World in Data COVID-19 Stringency Index (Hale et al., 2021). The index has daily scores for each state in 2020, ranging from 1 (least stringent) to 100 (most stringent), and summarizes 15 policy response indicators.[2] For the first-phase model, we use the average Stringency Index for the months corresponding to the first phase in each state, starting in March. We use the average index for March-December 2020 for the all-phases model. There is no clear a priori hypothesis about the relationship between the stringency index and beef-packing resilience.

Table 5 shows the descriptive statistics. We include the median to examine the skewness of the resilience indices and the proportion of plant sizes. The median is less than the mean in all cases, indicating skewness. The skewness is particularly high for the plant size variables, *Large*$_j$ and *Medium*$_j$, as some states house neither or only one, excluding the other.

A common practice of dealing with skewness is to log-transform the dependent variable to make the error distribution closer to normal. The log transformation also permits interpreting the regression as elasticities if the covariates are log-transformed or semi-elasticities if not. Although log-linear models could be helpful, they can result in biased and inconsistent estimates in the presence of heteroskedasticity (Motta, 2019; Santos-Silva and Tenreyro, 2006). Santos-Silva and Tenreyro (2006) show that a Poisson Pseudo-Maximum-Likelihood (PPML) estimation method can be employed to remedy this issue. In our case, the presence of zeros in the plant size variables, besides not permitting log transformation, may result in inflated standard errors, introduce heteroskedasticity, and affect the normality of the errors. Thus, we use the PPML regression instead of linear regression to estimate the model. In addition to addressing the heteroskedasticity that may arise from the presence of zeros in the plant size variables, PPML also eliminates the need

[2]The respective indicators are for virus containment, school closing, economic support, workplace closing, cancelation of public events, restrictions on gatherings, closing public transport, stay-at-home order, public information campaigns, testing policy, contact tracing, facial covering, protection of the elderly, confirmed cases, and confirmed deaths.

Table 5. Descriptive statistics

Variables	Mean	Median	Standard Deviation	Minimum	Maximum
$\mathcal{RES}^{Magnitude}_{1st\ phase}$	1.891	1.092	1.266	0.156	10.868
$\mathcal{RES}^{Magnitude}_{all\ phase}$	1.431	1.037	1.141	0.292	6.496
$\mathcal{RES}^{Speed}_{1st\ phase}$	1.922	1.028	2.756	0.182	12.199
$\mathcal{RES}^{Speed}_{all\ phase}$	1.658	1.185	1.243	0.288	5.562
$\mathcal{RES}^{Momentum}_{1st\ phase}$	13.371	1.233	33.714	0.035	163.230
$\mathcal{RES}^{Momentum}_{all\ phase}$	7.911	2.068	13.873	0.285	60.329
$\mathcal{RES}^{\mathrm{Force}}_{1st\ phase}$	5.287	1.973	12.079	0.030	62.654
$\mathcal{RES}^{\mathrm{Force}}_{all\ phase}$	3.224	1.672	5.599	0.282	31.863
Large	0.419	0.000	0.450	0.000	0.990
Medium	0.294	0.021	0.378	0.000	0.936
Small	0.205	0.046	0.303	0.000	1.000
Very small	0.080	0.004	0.237	0.000	1.000
$Stringency_{1st\ phase}$	0.852	0.853	0.084	0.648	0.999
$Stringency_{all\ phase}$	0.772	0.768	0.084	0.609	1.000
RTW (0/1)	0.628	1.000	0.490	0.000	1.000

to specify the distributional assumption of the resilience indices. We also apply state shares in the total U.S. cattle slaughter from the sample as weights for the PPML regression to improve efficiency. The shares range from 0.023 percent for Mississippi to 23.36 percent for Nebraska. The PPML specification transforms equation (6) into the following form:

$$\mathcal{RES}^{i}_{jk} = e^{\beta_{1k}+\beta_{2k}Large_j+\beta_{3k}Medium_j+\beta_{4k}Small_j+\beta_{5k}Difference_j+\beta_{6k}RTW_j+\beta_{7k}Stringency_j)} + \varepsilon_{ijk} \tag{7}$$

6. Results

The PPML results are in Tables 6 and 7. The estimates in Table 6 pertain to the first phase (peak-trough-peak) of cattle slaughter, which commenced in March 2020. The estimates in Table 7 capture multiple phases between March and December 2020. Due to the collinearity between *Large* and *Medium* variables (r = −0.6446), we ran six weighted PPML specifications for each resilience index. Each has a different treatment of plant size variables: Specification 1 includes *Large, Medium*, and *Small* variables, along with *RTW* and *Stringency*. Specifications 2, 3, 4, and 5 include separate variables for *Large, Medium, Small, and Very Small* plant sizes. Specification 6 consists of the *Difference* variable instead of the plant size variables.

The results in Table 6 reveal that during the first phase (the initial drop and rebound starting in March 2020 and ending in various months, depending on the state), neither the stringency of the states' responses nor the *RTW* status was significant in all specifications. While estimates for large plants in Specification 1 suggest that they are less resilient relative to the very small plants, the estimate in Specification 2 indicates a negative relationship between resilience and plant size across all four metrics (magnitude, speed, momentum, and force). The opposite is true for the medium, small, and very small plants (Specifications 3, 4, and 5). The results in Specification 6 reinforce the results in other specifications, as the estimate on the *Difference* variable indicates that the greater the reliance on larger plants relative to other plants in a state, the stronger the negative relationship with the resilience during the first phase of COVID-19 disruption. Lastly, judging by the R^2 value across metrics and specifications, the explanatory power of the covariates is higher when resilience is

Table 6. Weighted PPML resilience model parameter estimates for the first phase

	Magnitude						Speed					
Variables	1	2	3	4	5	6	1	2	3	4	5	6
Large	−1.742***	−1.134***					−1.074	−1.673***				
	(0.374)	(0.278)					(0.657)	(0.366)				
Medium	0.189		1.680***				0.881		2.281***			
	(0.444)		(0.343)				(0.774)		(0.489)			
Small	−2.836***			1.067*			0.0807			2.257***		
	(0.934)			(0.616)			(1.202)			(0.617)		
Very small					1.861***						1.700**	
					(0.423)						(0.668)	
Difference						−0.567***						−0.836***
						(0.139)						(0.183)
Stringency1	1.167	1.437	1.140	1.706	1.892	1.437	0.524	0.729	0.304	1.061	1.251	0.729
	(1.797)	(2.018)	(1.850)	(2.988)	(3.106)	(2.018)	(3.175)	(3.205)	(3.217)	(4.674)	(5.058)	(3.205)
RTW	0.128	0.176	0.139	0.163	0.147	0.176	0.306	0.335	0.264	0.348	0.259	0.335
	(0.141)	(0.163)	(0.145)	(0.242)	(0.253)	(0.163)	(0.429)	(0.426)	(0.432)	(0.532)	(0.564)	(0.426)
Constant	0.606	−0.267	−1.121	−1.577	−1.715	−0.834	0.00402	0.406	−0.841	−1.495	−1.552	−0.430
	(1.487)	(1.751)	(1.685)	(2.729)	(2.840)	(1.792)	(2.632)	(2.910)	(2.844)	(4.206)	(4.591)	(2.864)
Obs	35	35	35	35	35	35	35	35	35	35	35	35
R-squared	0.464	0.190	0.230	0.012	0.155	0.190	0.231	0.191	0.195	0.007	0.004	0.191

Table 6. Continued

	Momentum						Force					
Variables	1	2	3	4	5	6	1	2	3	4	5	6
Large	−3.181***	−3.503***					−1.791*	−1.227***				
	(0.666)	(0.509)					(0.977)	(0.423)				
Medium	0.722		4.541***				−1.489		0.979**			
	(0.825)		(0.638)				(1.009)		(0.408)			
Small	−0.608			4.140***			0.570			2.563***		
	(1.846)			(0.933)			(1.623)			(0.888)		
Very small					3.562***						2.300***	
					(0.737)						(0.572)	
Difference						−1.751***						−0.614***
						(0.254)						(0.212)
Stringency1	3.437	4.023	3.019	12.74	15.68	4.023	1.322	0.976	1.017	1.189	1.578	0.976
	(4.327)	(4.835)	(4.599)	(20.05)	(22.96)	(4.835)	(2.815)	(2.618)	(3.011)	(2.986)	(3.228)	(2.618)
RTW	0.803	0.931*	0.685	1.703	1.352	0.931*	0.502	0.427	0.384	0.508	0.399	0.427
	(0.489)	(0.554)	(0.546)	(1.690)	(1.826)	(0.554)	(0.396)	(0.396)	(0.433)	(0.409)	(0.447)	(0.396)
Constant	−0.448	−0.732	−3.115	−11.96	−14.06	−2.483	1.062	0.848	−0.345	−0.611	−0.813	0.235
	(3.587)	(4.476)	(4.182)	(18.50)	(21.18)	(4.423)	(2.552)	(2.599)	(2.762)	(2.715)	(2.971)	(2.484)
Obs	35	35	35	35	35	35	35	35	35	35	35	35
R-squared	0.340	0.274	0.292	0.001	0.060	0.274	0.100	0.042	0.004	0.058	0.133	0.042

Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Large = Proportion of the state's slaughter coming from plants with 1 and 10 million head capacity. Medium = Proportion of the state's slaughter coming from plants with 100k-999,999 head. Small = Proportion of the state's slaughter coming from plants with 10k-99,999 head. Very small = Proportion of the state's slaughter coming from plants with 1-9999 head. Difference = Difference in the state's share of large plants and the aggregate share of other plants. Stringency1 = The stringency index for the first phase 2020

Table 7. Weighted PPML resilience model parameter estimates for all phases

	Magnitude						Speed					
Variables	1	2	3	4	5	6	1	2	3	4	5	6
Large	−0.798***	−0.444**					0.140	−0.564**				
	(0.164)	(0.214)					(0.538)	(0.260)				
Medium	0.125		0.730**				1.256**		0.986***			
	(0.280)		(0.305)				(0.570)		(0.318)			
Small	−1.549***			0.285			−0.335			0.353		
	(0.506)			(0.446)			(0.945)			(0.545)		
Very small					0.807***						0.0791	
					(0.228)						(0.594)	
Difference						−0.222**						−0.282**
						(0.107)						(0.130)
Stringency2	0.889	1.114	0.958	1.207	1.199	1.114	−4.773***	−4.490***	−4.600***	−5.070***	−5.274***	−4.490***
	(3.182)	(3.143)	(3.144)	(3.487)	(3.534)	(3.143)	(1.517)	(1.585)	(1.513)	(1.722)	(1.693)	(1.585)
RTW	0.170	0.196	0.182	0.190	0.184	0.196	−0.581***	−0.546***	−0.559***	−0.614***	−0.640***	−0.546***
	(0.376)	(0.366)	(0.370)	(0.392)	(0.398)	(0.366)	(0.196)	(0.197)	(0.193)	(0.210)	(0.203)	(0.197)
Constant	0.0357	−0.510	−0.826	−1.006	−0.994	−0.732	3.932***	4.396***	3.922***	4.346***	4.525***	4.114***
	(2.631)	(2.679)	(2.572)	(2.863)	(2.904)	(2.624)	(1.238)	(1.285)	(1.245)	(1.419)	(1.387)	(1.289)
Obs	35	35	35	35	35	35	35	35	35	35	35	35
R-squared	0.278	0.018	0.124	0.073	0.008	0.018	0.281	0.098	0.255	0.045	0.057	0.098

Table 7. Continued

	Momentum						Force					
Variables	1	2	3	4	5	6	1	2	3	4	5	6
Large	−1.290	−2.014***					−1.128	−0.870**				
	(0.873)	(0.424)					(0.843)	(0.345)				
Medium	1.286		2.796***				−1.027		0.619**			
	(0.887)		(0.543)				(0.853)		(0.254)			
Small	−0.451			2.062**			0.706			1.925**		
	(1.743)			(0.836)			(1.402)			(0.842)		
Very small					1.460						1.486**	
					(1.067)						(0.711)	
Difference						−1.007***						−0.435**
						(0.212)						(0.173)
Stringency2	−4.427	−3.927	−4.885*	−6.045	−7.778	−3.927	−1.983	−2.432*	−3.003	−2.010	−3.000	−2.432*
	(2.879)	(3.123)	(2.901)	(4.766)	(4.760)	(3.123)	(1.318)	(1.395)	(1.898)	(1.360)	(2.033)	(1.395)
RTW	−0.379	−0.293	−0.443	−0.529	−0.797*	−0.293	0.00245	−0.0601	−0.139	0.00487	−0.157	−0.0601
	(0.324)	(0.342)	(0.333)	(0.457)	(0.461)	(0.342)	(0.238)	(0.238)	(0.270)	(0.240)	(0.270)	(0.238)
Constant	5.323**	5.601**	4.442*	5.494	7.054*	4.594*	3.083**	3.212**	2.863*	1.977*	2.887*	2.777**
	(2.107)	(2.347)	(2.415)	(3.909)	(3.897)	(2.464)	(1.247)	(1.281)	(1.603)	(1.143)	(1.702)	(1.214)
Obs	35	35	35	35	35	35	35	35	35	35	35	35
R-squared	0.282	0.139	0.315	0.009	0.002	0.139	0.162	0.060	0.002	0.155	0.017	0.060

Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.
Large = Proportion of the state's slaughter coming from plants with 1 and 10 million head capacity. Medium = Proportion of the state's slaughter coming from plants with 100k-999,999 head. Small = Proportion of the state's slaughter coming from plants with 10k-99,999 head. Very small = Proportion of the state's slaughter coming from plants with 1-9999 head. Difference = Difference in the state's share of large plants and the aggregate share of other plants. Stringency2 = The stringency index for March-December 2020.

measured in terms of magnitude and momentum. Since momentum measures the relative magnitudes and speeds of the drops and recoveries in relation to normal slaughter, it also encompasses other measures. Therefore, momentum is a suitable measure for assessing resilience in the industry during the initial drop and subsequent recovery from the COVID-19 pandemic.

The results for all phases in the March-December period (Table 7) are qualitatively similar to those in the first phase (Table 6) – the reliance on large (medium) plants has a negative (positive) relationship with all four resilience indices across the alternative specifications. While the relationship between small plants and resilience is significantly positive for momentum and force metrics, the estimates for very small plants are positive for magnitude and force metrics. This result aligns with the findings of Dhoubhadel et al. (2024), who reported a positive relationship between smaller plants and plant resilience during the pandemic. The negative relationship of *Stringency* and *RTW* variables with resilience is pronounced mainly for the speed metric. The metrics with relatively higher predictive power are speed and momentum. Given the nested nature of the momentum metric, it is also a good candidate for measuring resilience in the multiple-phase case.

In summary, the alternative resiliency models indicate that while states relying on larger plants with annual slaughter exceeding 1 million head were less resilient during the pandemic, states relying on medium-sized plants with slaughter between 100,000 and 1 million head were relatively resilient. The smaller plants (with an annual slaughter of less than 100,000 head), though resilient than the large plants, were not as resilient as the medium plants, when evaluated based on all four resilience metrics. That suggests that the USDA initiative to enhance resilience in the U.S. beef industry by focusing on smaller plants is narrow, given the resilience-enhancing role of medium plants. The results also suggest that, in light of the varying predictive power and nested nature of the resilience metric, the momentum metric best captures the degree of resilience during the 2020 supply disruption.

7. Summary, Conclusions, and Implications

This paper contributes to the retrospective literature on beef-packing resilience during COVID-19 by leveraging the heterogeneity in cattle slaughter across U.S. beef-producing states to compute resilience metrics for each state during the pandemic. It then examines how these metrics relate to each state's dependence on large plants, labor market conditions, and COVID-19-related policy measures.

We find that while reliance on large plants (with annual slaughter of 1 million and less than 10 million head) diminished the industry's ability to reduce the magnitude and duration of the pandemic shock to their beef processing, reliance on medium plants (with annual slaughter of between 100,000 and less than 1 million head of cattle) enhanced resilience. Although positive, the impact of smaller plants (with an annual slaughter of fewer than 100,000 head of cattle) on resilience is not as significant as in the case of medium-sized plants. Considering the varying predictive power and nested nature of the momentum metric, it may be the most appropriate metric for measuring resilience during the COVID-19 supply disruption.

The findings suggest that the current U.S. beef processing sector is less resilient to supply shocks such as COVID-19 because it relies heavily on large-scale plants. An implication for the USDA initiative is that its sole focus on expanding smaller plants to enhance resilience in the industry is too narrowly defined and may not achieve the intended effect on the industry's resilience, given the resilience-enhancing role of medium-sized plants. Moreover, promoting medium-sized plants may offer a more effective strategy for enhancing the resilience of the U.S. beef supply without significantly compromising scale efficiency, as would be the case if only small plants are targeted by the initiative.

However, given that the plant-size resilience relationship we estimate is unique to the pandemic period, one question is whether medium-sized incumbent and entrant plants can compete with the larger plants during normal times, given the significant economies of scale in beef packing. First, it depends on the type of cost structure of entering plants. Unless they are at least as cost-efficient as incumbent plants, they are just as vulnerable and may exit without further government subsidies during normal times. Second, the increased derived demand for cattle by new entrants shrinks the dominant packers' residual supply of cattle, weakening their market power, and raising cattle prices. Assuming the medium-sized plants behave as a competitive fringe (price takers), the rise in cattle prices due to weakened dominant market power ironically narrows the margins of medium-sized incumbents and entrants, speeding up the exit of less efficient firms. In the long run, the surviving medium-sized plants that would contribute to resilience in the event of another pandemic may be the more cost-efficient medium-sized plants that entered the industry with the help of the USDA initiative. As in the case of some past government subsidies to agriculture, if the spending hastens the adoption of new processing technologies, such as automation and the use of AI, for example, rather than simply replicating existing plants with old technology, then promoting medium-sized plants may be worth the government's investment.

Another challenge to the survival of both medium-sized incumbents and entrants is the benefits cattle feeders derive from forward contracting with larger plants, making it harder for smaller plants to secure a dependable cattle supply. In theory, forward contracting, as a variant of backward integration, would reduce the incentive of dominant packers to monopsonize the cattle market, possibly leading (counter intuitively) to a rise in the cash price of spot cattle; again narrowing margins for the medium-sized plants and speeding up the exit of the less cost-efficient ones. As a countermeasure, the USDA could incentivize feed yards to integrate with medium-sized plants, thus increasing profits for the feed yards and the plants.

More importantly, the competitiveness of medium-sized plants is not location-independent. They are less likely to survive in the leading cattle-producing states, where large plants dominate due to scale economies and contracts with feedyards, than in states in the Southeast, for example, where feedyards are smaller and more dispersed, offering less of a cost advantage to the larger packers. Medium-sized plants could also be more cost-effective if they specialize in niche beef products that do not require larger-scale plants. In summary, medium-sized plants could potentially be cost-competitive, depending on their technology, location, specialization, and integration through feed yard ownership of medium-sized packing plants.

Three caveats are worth noting, primarily due to data limitations. First, our analysis does not include all U.S. states due to USDA data disclosure restrictions and discontinuities in time-series data for some states, which reduces our sample to 35 states. Second, state-level cattle slaughter data are available only monthly. With this limited sample size, our study should be viewed as an illustrative exercise in constructing and modeling resilience metrics to assess the impact of plant size on the resilience of the U.S. beef-packing industry. Third, we rely on the midpoint of each slaughter category as a proxy for average plant slaughter volumes, which may introduce measurement errors. These limitations could be addressed in future research by replicating this exercise on high-resolution plant-level data.

Data availability statement. The data used in this research were collected from publicly available database sources. The data and codes used in this analysis are available on request from the authors.

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Appendix

See Appendix Tables A1 and A2.

Table A1. Calculated values of resiliency indices for the states (first phase)

States	Magnitude	Speed	Momentum	Force
Al	4.51	2.25	21.61	6.64
AR	1.82	0.30	0.95	0.73
AZ	0.18	0.18	0.04	0.03
CA	1.22	1.22	1.61	0.73
CO	0.90	0.30	0.58	2.51
ID	1.45	0.72	1.23	2.94
IN	4.28	4.28	20.98	3.98
KS	0.99	0.33	0.44	1.77
KY	10.87	10.87	163.23	13.75
LA	7.51	3.76	31.12	39.40
MD	1.15	0.38	0.57	2.06
MO	3.67	2.45	20.63	5.99
MS	1.15	1.44	3.30	1.35
MT	0.16	6.38	54.17	62.65
NC	1.08	1.08	1.33	2.56
ND	2.08	0.52	1.96	1.29
NE	1.03	1.03	1.76	3.46
NH	0.60	1.19	0.73	0.33
NJ	0.25	0.25	0.08	0.40
NM	1.09	1.09	1.23	0.59
NY	0.30	0.30	0.09	0.07
OH	0.69	1.03	0.89	0.44
OK	6.10	12.20	113.27	8.58
OR	1.95	2.92	11.42	2.91
PA	1.08	0.54	0.29	0.83
SC	0.65	0.33	0.23	0.93
SD	1.33	0.44	0.69	2.24
TN	1.15	1.15	1.73	3.23
TX	0.79	0.79	0.87	1.97
UT	1.45	2.07	2.58	3.83
VA	1.04	2.89	4.52	1.16
WA	0.73	0.36	0.42	1.58
WV	0.73	0.97	1.28	0.65
WI	1.21	0.60	1.05	2.78
WY	1.03	0.65	1.15	0.70

Table A2. Calculated values of resiliency indices for the states (all phases)

States	Magnitude	Speed	Momentum	Force
Al	6.50	4.81	60.33	9.85
AR	1.47	0.29	0.75	0.66
AZ	1.23	1.39	2.54	2.43
CA	0.71	1.11	1.34	0.73
CO	1.03	1.23	1.77	2.07
ID	0.79	0.86	0.77	1.31
IN	1.52	2.42	6.55	1.40
KS	1.63	0.72	1.62	1.67
KY	2.72	3.24	36.60	3.44
LA	2.60	1.44	10.43	13.22
MD	1.06	0.90	1.19	1.69
MO	2.29	1.61	11.52	3.59
MS	1.15	1.44	3.30	1.35
MT	0.80	3.31	27.21	31.86
NC	1.24	1.86	3.17	2.80
ND	1.74	0.87	2.07	2.10
NE	0.76	0.68	0.93	1.80
NH	0.29	0.56	0.29	0.28
NJ	3.37	3.97	30.64	5.35
NM	0.91	0.67	0.93	2.08
NY	0.60	0.88	0.82	0.72
OH	0.90	1.09	1.18	1.10
OK	2.78	5.56	40.03	3.68
OR	2.16	2.30	8.66	3.05
PA	1.14	0.69	0.54	0.83
SC	0.64	0.95	0.75	1.05
SD	1.36	1.65	3.25	1.57
TN	0.39	0.58	0.51	0.84
TX	0.92	1.19	1.26	1.30
UT	1.02	2.43	4.96	2.44
VA	1.04	2.89	4.52	1.16
WA	1.03	1.70	2.19	1.19
WI	0.79	0.97	0.87	1.29
WV	0.73	0.97	1.28	0.65
WY	0.81	0.83	2.16	2.31

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