Food Policy 119 (2023) 102522

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

Econometric assessment of the effects of COVID-19 outbreaks on U.S. meat production and plant utilization with plant-level data[☆]

Joseph Cooper[a,*], Vincent Breneman[a], Meilin Ma[b], Jayson L. Lusk[b,d], Joshua G. Maples[c], Shawn Arita[a]

[a] USDA, USA
[b] Department of Agricultural Economics, Purdue University, USA
[c] Department of Agricultural Economics, Mississippi State University, USA
[d] Oklahoma State University, USA

ARTICLE INFO

Keywords:
Meatpacking
Livestock
Cattle
Swine
Broilers
COVID-19

ABSTRACT

This paper quantifies the impact of the COVID-19 disruption on U.S. meatpacking production. We employ a confidential plant-level meatpacking plant data set from USDA that gives daily livestock (cattle, swine, broilers) slaughter by individual firms and their individual plants. We found a larger underutilization rate of processing capacity for larger-sized beef and pork plants during the peak of plant slowdowns in April-May 2020, while no such relationship was found for broiler plants. In our panel analysis of beef packing plants, we found that higher COVID-19 infection rates in a county were associated with greater plant disruptions, but that plants appear to have been able to adjust relatively quickly to these disruptions. Our empirical analysis suggests a beef plant distribution with fewer large plants could have meant smaller shocks to production during the initial surge of COVID-19 disruptions. However, beef plant size was significantly less important to maximizing utilization of processing capacity after the initial surge.

1. Introduction

The U.S. food system experienced significant impacts due to the COVID pandemic. Within the food system, meat supply chains were among the most disrupted sectors. Starting in early March 2020, meatpacking plants and processors of poultry, pork, and beef were forced to scale back production or temporarily close as COVID-19 spread through the workforce (Balagtas and Cooper, 2021; Lusk et al., 2021; Martinez et al., 2021). According to a congressional report, between March 1, 2020, and February 1, 2021, roughly 59,000 meat workers contracted the coronavirus, and deaths totaled at least 269 (Congress, 2021). Rural counties dependent on meatpacking experienced COVID-19 rates almost 10 times higher than other rural counties not dependent on meatpacking (Krumel and Goodrich, 2022).[1]

The resulting illness, or fear of illness, contributed to absenteeism among plant workers. Moreover, some plants were forced to temporarily close to prevent spread of the pandemic virus. Plants remaining open slowed production lines in order to comply with public health guidelines for reducing COVID-19 spread (e.g., social distancing). As plants were idled or forced to limit operations, daily capacity at U.S. cattle and hog facilities declined by as much as 45 percent in May 2020 relative to May 2019 (Cowley, 2020). Slaughter rates rebounded by June 2020 (Vaiknoras et al., 2022). For example, by mid-June, capacity utilization in pork processing plants rebounded to near 95 percent, and increases in consumer price dissipated (Haley, 2020).

Partial plant closures and increased social distancing protocols were implemented at meatpacking plants across the country starting in late April 2020 through early June. These preventative measures appear to have had some effect on infection rates, as late May/early June saw the beginning of a sharp reduction in the number of new cases per 100,000 for these meatpacking-dependent counties relative to manufacturing dependent counties. At its peak the ratio of the two-week moving

☆ *The findings and conclusions in this paper are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.*

* Corresponding author at: U.S. Department of Agriculture, 1400 Independence Ave, S.W., Washington, DC 20250, USA.
E-mail addresses: joseph.cooper@USDA.gov (J. Cooper), vince.breneman@usda.gov (V. Breneman), mameilin@purdue.edu (M. Ma), jlusk@purdue.edu (J.L. Lusk), josh.maples@msstate.edu (J.G. Maples), shawn.arita@usda.gov (S. Arita).

[1] Using topographic regression methods, Saitone et al. (2021) also find that counties with large meat packing plants experienced significantly higher levels of infections—110% per capita infection rates for beef and 160% for pork relative to similar counties without meatpacking plants.

https://doi.org/10.1016/j.foodpol.2023.102522
Received 26 August 2022; Received in revised form 1 August 2023; Accepted 6 August 2023
Available online 15 September 2023
0306-9192/Published by Elsevier Ltd.

average of new daily cases per 100,000 population between rural meatpacking and manufacturing dependent counties was over 12, but fell to 1 by late July 2020 (Krumel and Goodrich, 2022).[2]

This paper econometrically assesses the impact of the COVID-19 disruption on U.S. meatpacking production based on unique plant-level data. There has been much attention in the popular press and academic study to the role of COVID-19 on meat packing plants. Previous studies have provided descriptive evidence showing the impacts of the disruption (Balagtas and Cooper, 2021). Other studies have econometrically examined the relationship (Saitone et al., 2021; Bina et al., 2022). However, these have had to employ county-level data on COVID-19 infection rates and packing plant locations. Instead, we employ a confidential plant-level meatpacking plant data set from USDA that gives daily livestock (cattle, swine, broilers) slaughter by individual firms and their individual plants. While regionally aggregated production and capacity data are publicly available from USDA, our plant-level data allow for a more detailed analysis with less aggregation bias.

We estimate the impact of COVID-19 on daily slaughter and plant utilization metrics via a rigorous panel estimation strategy, controlling for a set of relevant market factors and shocks. Specifically, we explore the relationship between slaughter with COVID-19 infection metrics (e.g., cases, hospitalization, deaths) across counties and times, so that we may exploit spatial and time variation. We employ several dependent variables that measure the degree (e.g., percent loss) of the plant's loss in slaughter quantity relative to its capacity. The following empirical questions are addressed:

1. What has been the quantified impact of COVID-19 on meatpacking production and plant utilization?
2. How did the COVID-19 effect evolve across time?
3. Have some types of firms or plants (e.g., small sized) performed better than other types?
4. What is the quantitative relationship between beef plant size and resilience towards COVID-19 disruptions?

We contribute innovative research and new insights on impacts of COVID-19 disruptions using previously unexplored confidential micro-level data. To our knowledge, this paper is the first to examine plant-level impacts of the COVID-19 disruptions on cattle production and utilization. Our findings inform policy makers interested in promoting policies using federal and state investments in expanding small and mid-sized packing capacity by providing analysis of resiliency impacts associated with plant size.

2. Background

Figs. 1 through 3 summarize yearly streams of national-level data on federally-inspected processing for cattle, hogs, and broilers over 2018–2022. Most of the dips and peaks are cyclical in nature. The peaks usually appear before the Labor Day, 4th of July, Christmas, and New Year's Day holidays due to demand increases, and the dips come on the holidays themselves as most plants take holidays off. However, the cattle and hog charts show major dips in April/May/June 2020 relative to the other years which are indicative of COVID-related plant slow-downs and shutdowns (see Figs. 1 and 2). Cattle and hog packing largely rebounded to typical patterns circa July 2020, and hog production tended to be above 2019 levels the rest of the year.

On April 28, 2020, the President issued an executive order invoking the Defense Production Act to keep meat-packing plants open (United States Department of Agriculture, 2020). The executive order exempted plants from state and local orders to close nonessential businesses, but did not solve plants' problems with sick workers. COVID-19 outbreaks among the workforce continued to force plants to close and slow down even after the Executive Order. However, the bulk of the COVID-related slowdowns and shutdowns were relatively short-lived. Processing recovery that took place later in early summer through September may have been facilitated by plants aggressively implementing many safety protocols to prevent the spread of COVID-19, such as requiring face coverings, educating workers on community spread, staggering shifts, testing workers, and installing physical barriers between workers (Waltenburg et al., 2020; NAMI, 2021).

Herstein et al. (2021) found that 8 of the 13 packing plants they studied had a statistically significant reduction in COVID-19 incidence within 10 days of initiating universal mask policies and installing physical barriers. Rapid protocols such as these may account for why COVID cases among packer employees started a downward trend May to August 2020 while cases in the general population trended up over that period (NAMI, 2020). Krumel and Goodrich (2022) found that the difference in COVID infection rates between meat packing dependent rural counties and nonmeat packing counties evaporated by mid-2020 and suggest from collating evidence that increased precautions to protect workers explains why the differences disappeared.

Broiler processing in 2020 did not display any strong negative shocks compared to the same months in previous years (see Fig. 3). According to Lusk et al. (2020), the reasons that broiler slaughter did not suffer the same declines in the first half of 2020 relative to cattle and hog slaughter may be attributed to higher automation, lower worker density, and the geographic location of plants. The dip in broiler production in February 2021 on account of freezing weather at the time appears to have been a bigger shock than any dips in 2020.

3. Data

Bina et al. (2022) examined the performance of the beef processing industry during the early stages of the COVID-19 pandemic, using aggregate data. The authors find limited statistical evidence for pandemic-induced production reductions being different for varying levels of regional reliance on larger processing facilities for most of 2020, and suggests 'caution' in the plant size to resilience relationship. While the study represents an important initial empirical treatment of pandemic-induced production reductions, validation of such results requires the use of the plant-level data to avoid aggregation bias and more explicit quantification of the role of plant size.

We use daily plant-level data covering April 6, 2020 through January 18, 2022, which were supplied by packers to the USDA's Agricultural Marketing Service (AMS).[3] This confidential database contains daily production and daily "normal" production for each weekday, and plant capacity. Capacity is the maximum ability of the plant to produce on any given day given its physical construction and design, and is hence a physical/engineering measure. Plants provide AMS with new capacity values when they do an alteration to the plant that changes its capacity. The data cover 33, 41, and 111 cattle, hog, and broiler packing plants and represent 74%, 91%, and 72% of all U.S. federally inspected slaughters, respectively in 2021. The excluded plants are smaller ones not required to report to AMS. Indeed, the estimated shares of total U.S. production by plants covered by our dataset might be underestimated as

[2] Krumel and Goodrich (2022) define a county as dependent on a single industry if said industry employs 20 percent or more of the county's total workforce. The comparison cited in the text compares rural counties with employment rates of 20% or more in meatpacking to rural counties with employment rates of 20% or more in other single manufacturing industries.

[3] This daily data on reports complied from the plants does not exist before April 6, 2020 as until that date, USDA-AMS discarded this data on a moving basis after examination. As plants got largely back to normal in 2021, 2021 and early 2022 data serve as the state of normal operation data to compare to the height of COVID impacts in 2020.

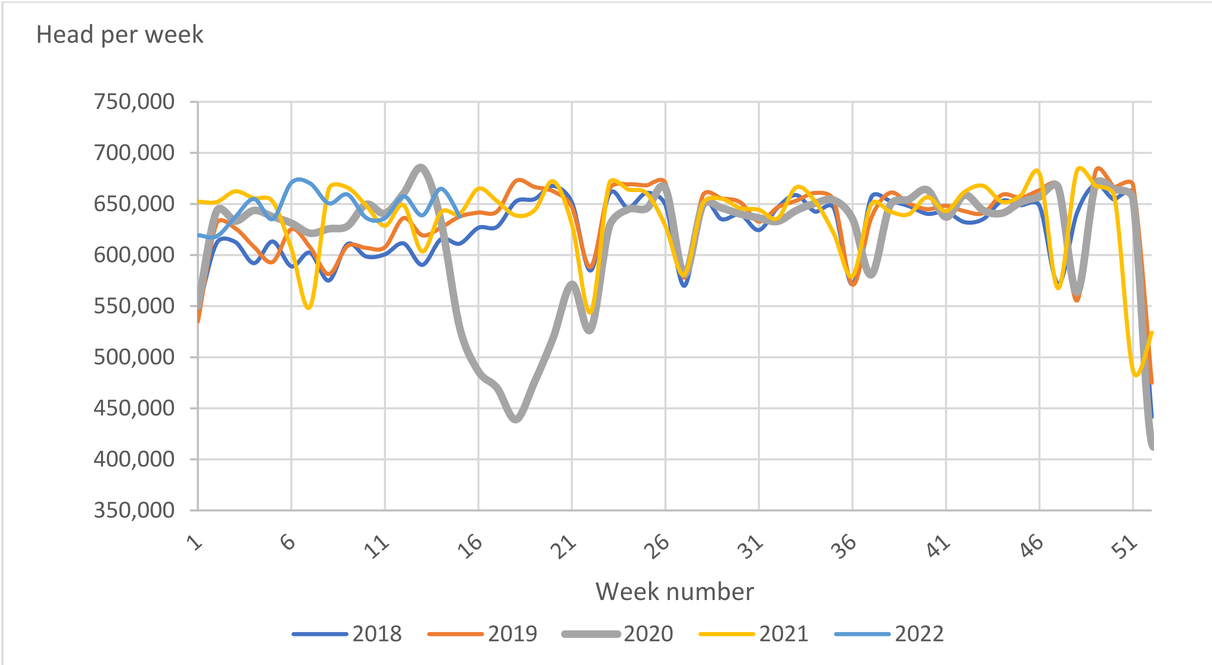

Fig. 1. Federally inspected cattle slaughter (weekly) Sources for Figs. 1 to 3: Quickstats, National Agricultural Statistics Service, USDA.

they do not include weekend slaughter, which large-sized plants tend to conduct when facing demand peaks or supply shortages.[4]

4. Econometric analysis

In this section, we use the unique plant-level dataset to examine COVID impacts on plant operation. We first define the key variables and particularly study the correlation between plant capacity and the average underutilization rate of a plant for each commodity to drive home some basic intuitions. Next, we formally set up the econometric specifications and report the econometric outcomes. Some sensitivity tests are conducted to confirm the baseline findings.

4.1. *Plant underutilization rates – aggregated over time*

Our goal is to identify factors that determine the degree and intensity of COVID impacts on plant operation. We define the key dependent variable, plant i's *underutilization* as ($current\ production_i - capacity_i$)/$capacity_i$, where production and capacity are in terms of head slaughtered, and where plant capacity is an engineering/physical measure of packing ability per day. Hence, the more negative the value is, the greater the underutilization of the plant. The dataset has this information necessary to do this calculation on a daily basis for each packing plant on weekdays. From April 6, 2020 through January 18, 2022, for cattle, hogs, and broilers, the mean of plant-level *average underutilization capacity* was −0.091 (standard deviation 0.056), −0.063 (standard deviation 0.068), and −0.029 (standard deviation 0.053), respectively.

We are particularly interested to test whether plants of different sizes experienced different rates of underutilization under COVID, because the size of plants is often discussed in policies and research aimed at boosting the resilience of meatpacking industry (e.g., Ma and Lusk, 2021). We hence use the daily *capacity* of each plant as the key explanatory variable in the regression. For cattle, hogs, and broilers, the mean of *capacity* is 3,106 (standard deviation 1,704), 11,602 (standard deviation 7,779), and 244,473 head (standard deviation 90,805), respectively.

Each livestock commodity has two regressions, one for the averages across the entire period, and one during the major shock period (for cattle and hogs) over April-May 2020, the approximate period for high levels of plant shutdowns or slowdowns related to COVID-19 infections. Over this period, mean plant-level *average underutilization capacity* was −0.224 (standard deviation 0.145), −0.206 (standard deviation 0.155), and −0.042 (standard deviation 0.069) for cattle, hog, and broiler plants, respectively. Comparison of these value for those above for April 2020-January 2022 show that mean plant-level *average underutilization capacity* for cattle, hogs, and poultry was significantly more negative (i.e., greater production shocks) during April-May 2020, but with the least impact for broilers. In particular, the ratios of the April 2020-May 2020 shocks to the April 2020-January 2022 average shocks was 2.5, 2.3, and 1.4 for cattle, hogs, and broilers, respectively.

The complete shut-down (i.e., no production) rates are broadly consistent with the underutilization rates. The shut-down rate − instances of complete daily shutdowns divided by total plant days − for cattle, hog, and broiler packing plants over April 2020-May 2020 (April 2020-January 2022) was 6.1% (1.6%), 8.1% (1.5%), and 2.1% (1.1%), respectively. Hence, the largest difference was for hogs and the smallest for broilers.

Beyond plant size distributions, the available data does not provide much in the way to support speculation over why broiler plant utilization was apparently less impacted by COVID than for swine and cattle. In addition to the reasons noted above in Lusk et al. (2020), another possibility could be that perhaps a significant number of broiler plants continued to operate in April-May 2020 despite COVID transmission among employees on the floor; broiler packing plants have even less leeway to delay processing before the animals get too large than do hog or beef packers.

[4] Saturday slaughter can be considered as a catch-up day, including to make up for holiday shortened weeks. Plants are usually not slaughtering on Sundays. On average, Saturday slaughter is lower than on a weekday – around 8 percent of weekly slaughter over 2015–2019 – as can be seen in the data in Maples (2021). The rule of thumb in the Agricultural Marketing Service is 5.4 days of beef packing per week, with the 0.4 being Saturday, a result not far off from that drawn from the Maples paper. We assume that plants that had slow-downs or shutdowns on Monday-Friday on account of COVID would also have done so on the adjacent Saturday. Hence, we do not expect a major impact of the omission of the Saturday shift on our results.

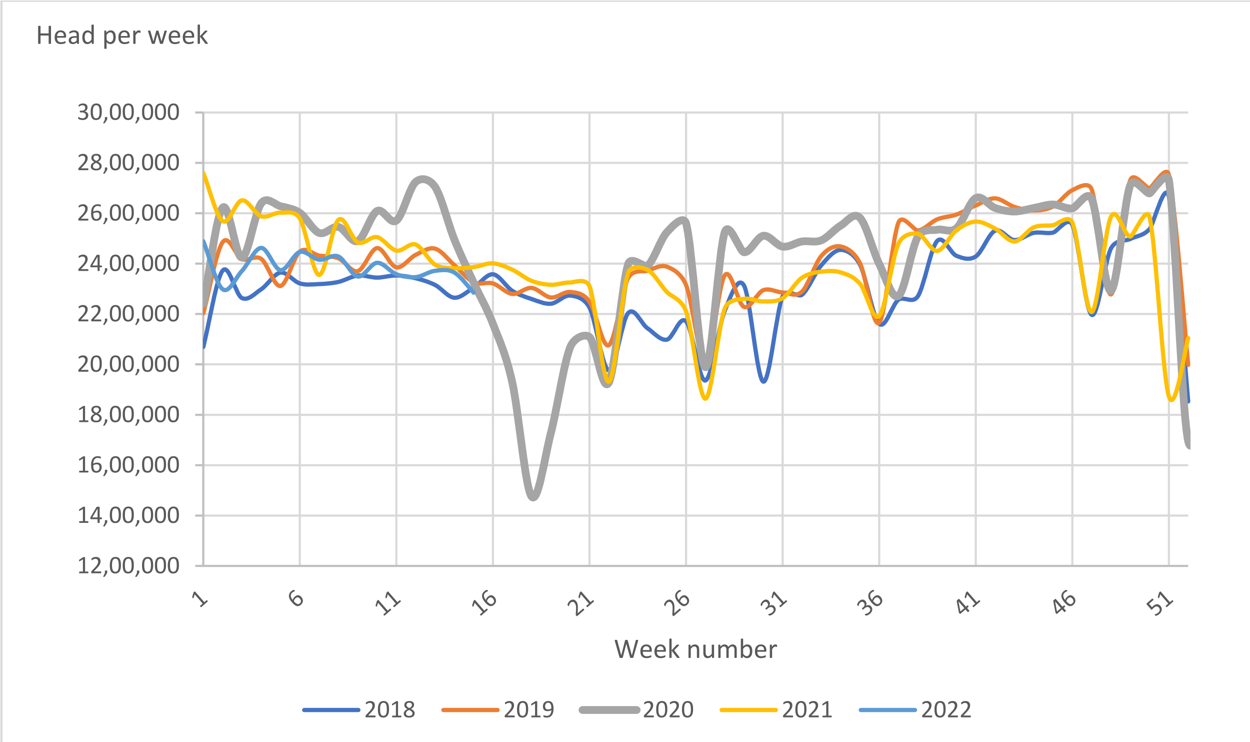

Fig. 2. Federally inspected hog slaughter (weekly).

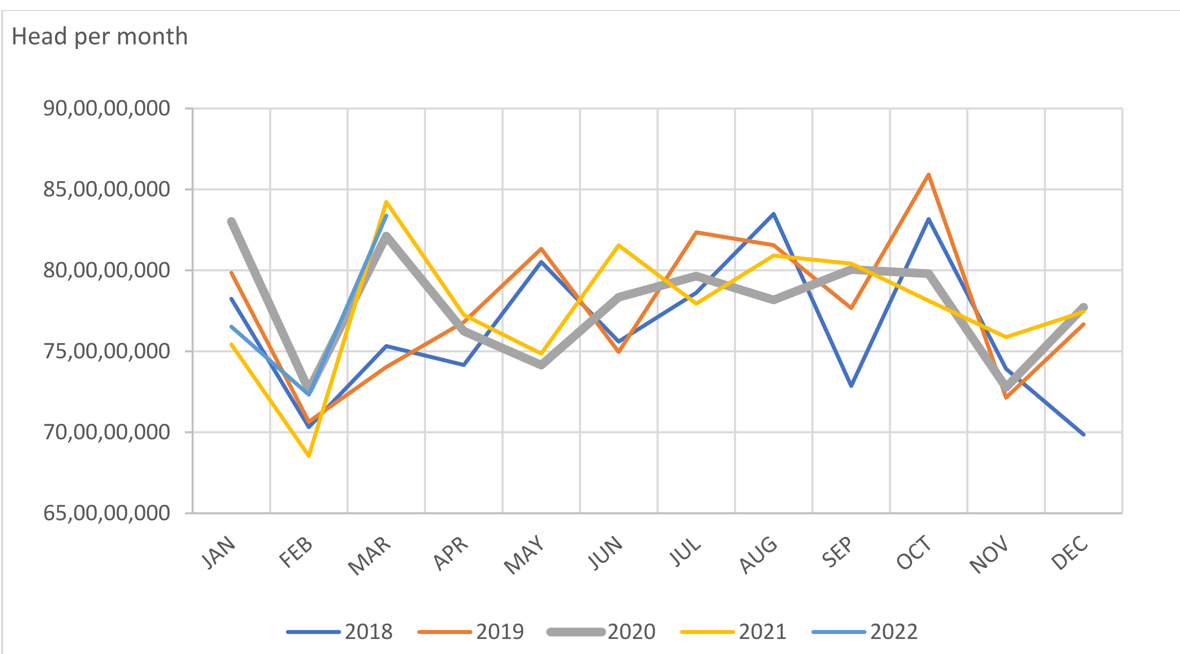

Fig. 3. Federally inspected broiler slaughter (monthly).

Regression analysis to explain the plant underutilization should explicitly account for the dependent variable being defined over $0 \leq y_i \leq 1$ in order to keep predictions within that space.[5] We use the fractional logit approach (Papke and Wooldridge, 1996, 2008) to achieve this. Let the population model $\Phi(x_i'\beta) = E(y_i|x_i)$ be a monotonic transformation that is bounded in the range 0 to 1. The transformation can conceivably be any number of models, but we assume $\Phi(\bullet)$ to be the logistic distribution per Papke and Woodridge (*ibid.*). The log likelihood function is $lnl(\beta) = \sum_{i=1}^{N}[y_i \ln\Phi(x_i'\beta) - (1 - y_i)\ln(1 - \Phi(x_i'\beta))]$, which is similar to the logit or probit regression model but with y_i falling in the range $0 \leq y_i \leq 1$ rather than being a dichotomous indicator variable [0,1]. The fractional logit model can be estimated via common statistical software, such as in STATA® with the Generalized Linear Model (GLM) approach with

[5] Note that the boundaries [0,1] on *underutilization* represent corner solutions and not censoring or truncation.

Table 1
Plant-level average underutilization rate as a function of the plant's capacity over the time period.

	Cattle		Hogs		Broilers	
	April 2020-Jan 2022	April-May, 2020[a]	April 2020-Jan 2022	April-May, 2020[a]	April 2020-Jan 2022	April-May, 2020[a]
			OLS (dep var = *average underutilization*)			
Intercept	−0.111***	−0.082*	−0.054***	−0.087**	−0.028*	−0.019
	(0.020)	(0.046)	(0.020)	(0.040)	(0.0146)	(0.019)
Average Plant Capacity	0.642	−4.686***	−0.337	−4.775***	−0.126	−2.54
	(0.589)	(1.32)	(0.679)	(1.337)	(1.516)	(1.687))
Adj. R^2	0.005	0.266	−0.020	0.232	−0.009	0.006
			Fractional logit (dep var = − *average underutilization*)			
Intercept	−2.060***	−2.065***	−2.841***	−1.974***	−3.524***	−0.0282***
	(0.292)	(0.306)	(0.337)	(0.201)	(0.226)	(0.009)
Average Plant Capacity	−8.189	25.643***	5.412	24.042***	3.076	−0.126
	(6.702)	(7.430)	(7.627)	(6.273)	(23.908)	(1.017)
Deriv. Average Plant Capacity[b]	0.677	−4.318***	−0.318	−3.870***	−0.0878	−1.851
	(0.604)	(1.141)	(0.424)	(1.061)	(0.688)	(1.087)
McFadden Pseudo R^2	0.013	0.244	0.002	0.215	0.000	0.005
Obs.	33	33	40	40	111	111

Note: The plant's capacity for these regressions was measured as a share of total sector capacity. [a]The number of observations is the number of plants that report data to AMS, and each observation was generated by taking the average for that plant's reports over the time span in question. [b]The coefficient is shown as the derivative of the function to allow comparison to the OLS coefficient. The sign of dependent variable is reversed from the actual estimated value to facilitate comparison to the OLS estimate given that the fractional logit estimation assumes $0 \leq y \leq 1$. The delta method was used to obtain the standard error of the derivative. Standard errors are in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

logistic link function. To allow for an interpretation of the coefficients that are comparable those of a standard linear model, it is convenient to interpret the regression results for continuous variables as derivatives with respect to x_i, or $\partial E(y_i|x_i)/\partial x_i = \beta\phi(x_i'\beta)$, where the scale factor $\phi(\bullet)$ is the logistic probability density function in this case.

Table 1 presents the fractional logistic and ordinary least square regressions of plant's average underutilization rate as a function of the plant's capacity over a given period.[6] The number of observations is the number of plants that report data to AMS, and each observation was generated by taking the average for that plant's reports over either the 454 weekdays from April 6, 2020 through January 18, 2022, or over the number of weekdays covered by the major shock period. Results for the OLS regressions are similar to those of the fractional logistic.

Considering the full time span of data, the average plant capacity does not have a statistically significant impact on the plant's average underutilization rate. However, for both hogs and cattle during the major shock period, the underutilization rate tends to be larger for larger sized plants.[7] This relationship is statistically significant and similar for both cattle and hogs during the peak of COVID slow-downs and shutdowns in April-May 2020. In contrast, for broilers, the relationship between the average underutilization rate and average plant capacity was statistically insignificant even during the major shock period for COVID.

Figs. 4 to 7 show the relationship between the capacity underutilization rate and plant capacity graphically, where each dot represents a plant. Fig. 4 (cattle and hogs) and 6 (broilers) cover the whole of April 6, 2020 through January 18, 2022. For hogs, the average underutilization rate is increasing (in the absolute value sense) as plant size increases, and the reverse for cattle, but as Table 1 shows, the slopes of the fitted lines are not significantly different from zero. The average underutilization rate for broilers is invariant to plant size.

Fig. 5 shows that during the peak of the COVID shock, the average underutilization rate for hog and cattle plants was increasing (in the absolute value sense) as plant size increases, and the relationship is markedly stronger (and statistically significant per Table 2) than over the full time span of the data. Put differently, production of larger plants tended to be relatively more negatively impacted as plant size increased during the peak of COVID spread. Comparison of Figs. 5 and 7 shows than for broilers, the capacity underutilization rate was invariant to average plant capacity both over the full time span of the data and also during April-May 2020, echoing the regression results in Table 1.

4.2. Plant underutilization rates under extreme shocks – pooled time series-cross section regression analysis

The preliminary examination in the previous sub-section utilized data consisting of the average of utilization rate of each plant across time. However, this approach potentially suffers from temporal aggregation bias and does not facilitate adding useful control variables. We hence turn to inter-temporal analysis of the individual plants over April 6, 2020 through January 18, 2022, focusing on cattle plants for the sake of brevity.

In addition to plant $underutilization_{it}$, we examine $underperformance_{it}$ for plant i and day t, which is ($current\ production_{it} - normal\ production_{it}$)/$normal\ production_{it}$, where *normal production* for this plant is what the plant reports to AMS as being "normal". This variable is also available for each plant on a daily weekday basis. The *underperformance* variable is perhaps a less precise variable than *underutilization* as a plant is not required to follow a strict statistical protocol in the definition of *normal production*.

Table 2 provides the descriptive statistics for the variables used in the econometric analysis as well as variables used to construct the regression variables. In addition to daily plant capacity, among the variables we include are daily dummies to control for time-invariant daily effects, such as Monday's being off to a slower start production wise, as well as a holiday dummy in the case that holidays affect production. Company (e.g., Tyson), monthly, and year fixed effects are also included. The principle for the company fixed effects is that plants under the same ownership may exhibit a similar response to shocks and market indicators in general. The S&P500 index is included to capture some common demand variation. COVID-19 impacts are modelled via *CovRtp*, the county-level seven day moving average of COVID-19 cases for the county in which the plant resides.

We perform two sets of regressions: Table 3 with *underutilization* (uu_{it}) as the dependent variable and Table 5 with *underperformance* as

[6] Note that none of the plants in the dataset reported their daily capacity changing over the time span of the data.

[7] The result for hogs is consistent with that of Padilla et al. (2023), which examined impacts of COVID on hog plants.

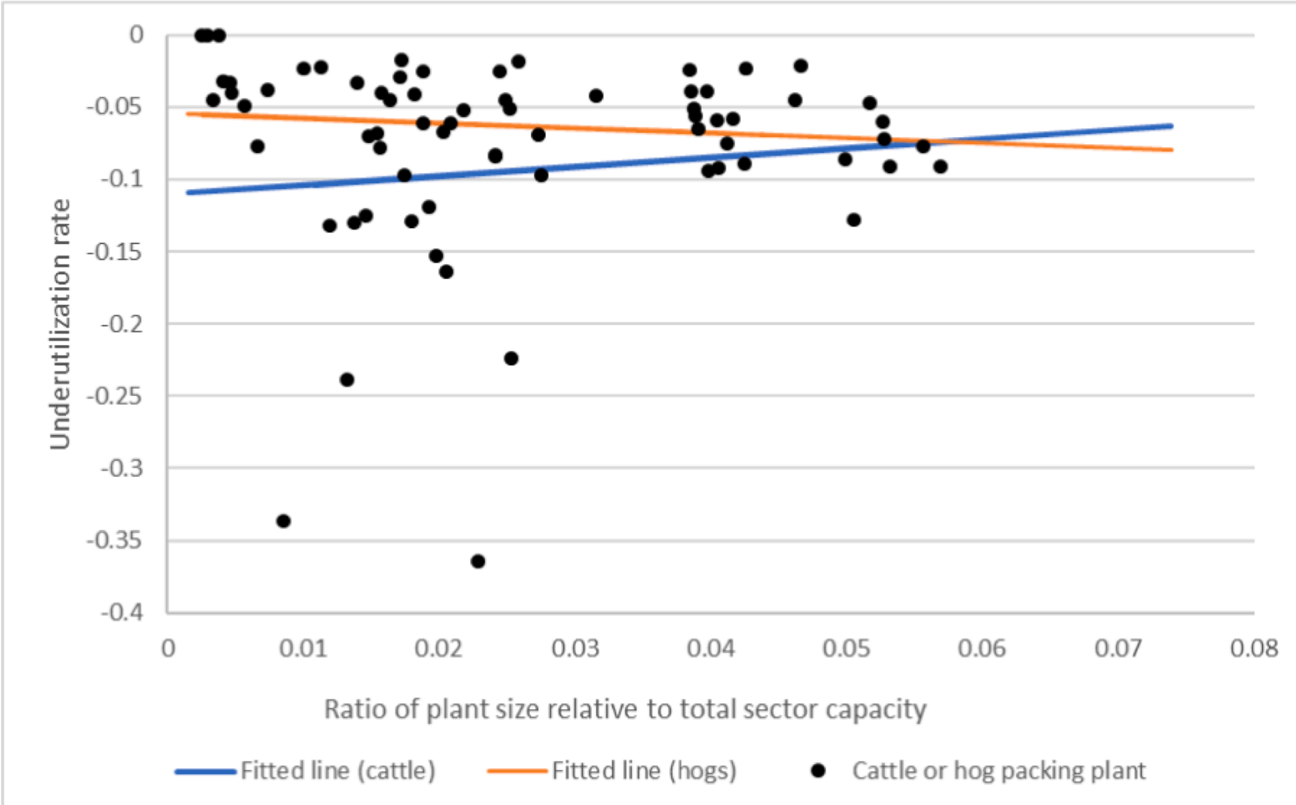

Fig. 4. Hog and cattle plant average underutilization rate relative to production capacity (April 2020 to January 2022) *Note*: For charting of the individual plant values in Figs. 4–7, but not for the fitted lines, normally distributed noise with mean zero has been added in generating the X-axis values in order to obscure confidential data. Also, to ensure confidentiality, markers for several plants have been omitted from each chart, but all the data were included in the regressions for the fitted lines.

the dependent variable. As in the previous section, we use the fractional logit estimation approach, but with the data disaggregated across days, over a logistic function $\Phi(uu_{icst})$ where uu_{icst} is expressed as:

$$uu_{icst} = a + \beta pc_i + \gamma CovRtp_{it} + \delta \text{SPXindex}_t + T_t + S_s \times M_t + C_c + e_{it} \quad (1)$$

where T_t is a vector of time fixed effects (weekday dummies to capture within week effects, and 12 month dummies to capture seasonality effects), $S_s \times M_t$ is a vector that interacts state fixed effects with dummy variables for each of the 22 months in the sample to allow the evolution of state effects over time, and C_c a vector of company effects (dummies reflecting multiple plants being under the same company ownership). Subscript $i = 1,\ldots,I$ plants (33 cattle plants), and subscript t indicates weekdays from April 6, 2020 through January 18, 2022. As plant capacity did not change for any plant over the timespan of the analysis – note that it is an engineering/physical measure of packing ability per day, pc_{it} effectively reduces to pc_t. The S&P index is added as a control for economic activity at the macro level – we expect a positive sign on its coefficient, i.e., an increase in the S&P index is a proxy for demand, and perhaps even supply factors, that lessen the probability of production shocks. The error term is denoted e_{it}.

For $CovRtp_{it}$, the subscript i denotes the county that plant i resides in. The only panel variable in the regression is $CovRtp_{it}$. For estimation of the coefficient on this variable over panel data to be unbiased and consistent in the fractional logit we include the time averages of $CovRtp_{it}$ and cluster the standard errors using the plant identifiers per Papke and Woolridge (2008), with this model being implemented in Stata®. We add a simple linear model with robust standard errors for comparison. Tables 3 and 4 show both ordinary least squares and fractional logistic outcomes. For Table 3 we also add a specification with quadratic effects for the continuous variables. For the fractional logit regressions, the results for the continuous variables are shown as derivatives as described in the previous section, while the results for the discrete variables are shown as discrete changes $\Phi(x^{(1)}\beta) - \Phi(x^{(0)}\beta)$, where $x^{(1)}$ and $x^{(0)}$ are different values of the variables (e.g., Papke and Woodridge, 2008).

The OLS and fractional logit coefficient results in Table 3 are generally in the same ballpark in spite of the differences between the two approaches. The coefficient(s) on *plant capacity* is negative and significant, meaning that the larger the plant, the greater the underutilization rate.[8] The effect is less than unitary elasticity, however. Likewise, the coefficient on *CovRtp* is negative and significant in all the models, meaning the higher the COVID infection rate the county, the greater the underutilization, or plant disruption.[9] The coefficient on *DefensePA* (dummy variable equaling 1 for April 28, 2020 and after, covering the period after the Defense Production Act was invoked) is insignificant. The positive coefficient on the S&P indicates smaller production shocks as the index increases, as expected. For the fractional logistic regression there is a mild benefit of adding the quadratic terms: based on likelihood ratio tests, the hypothesis of no quadratic effects is rejected at the 2.5% level of significance. For the OLS model however, the hypothesis of no quadratic effects is rejected at the one percent significance level.

Results in Fig. 1 and Table 1 suggest the possibility of a structural break in the plants' response to COVID-19 occurring in late Spring to early Summer 2020. We examine the break point by using an

[8] For the fractional logit, the net derivative over the base plant capacity and the squared value is −0.033 evaluated at the variable means.

[9] For the fractional logit, the net derivative over the base COVID value and the squared value is −0.591 evaluated at the variable means.

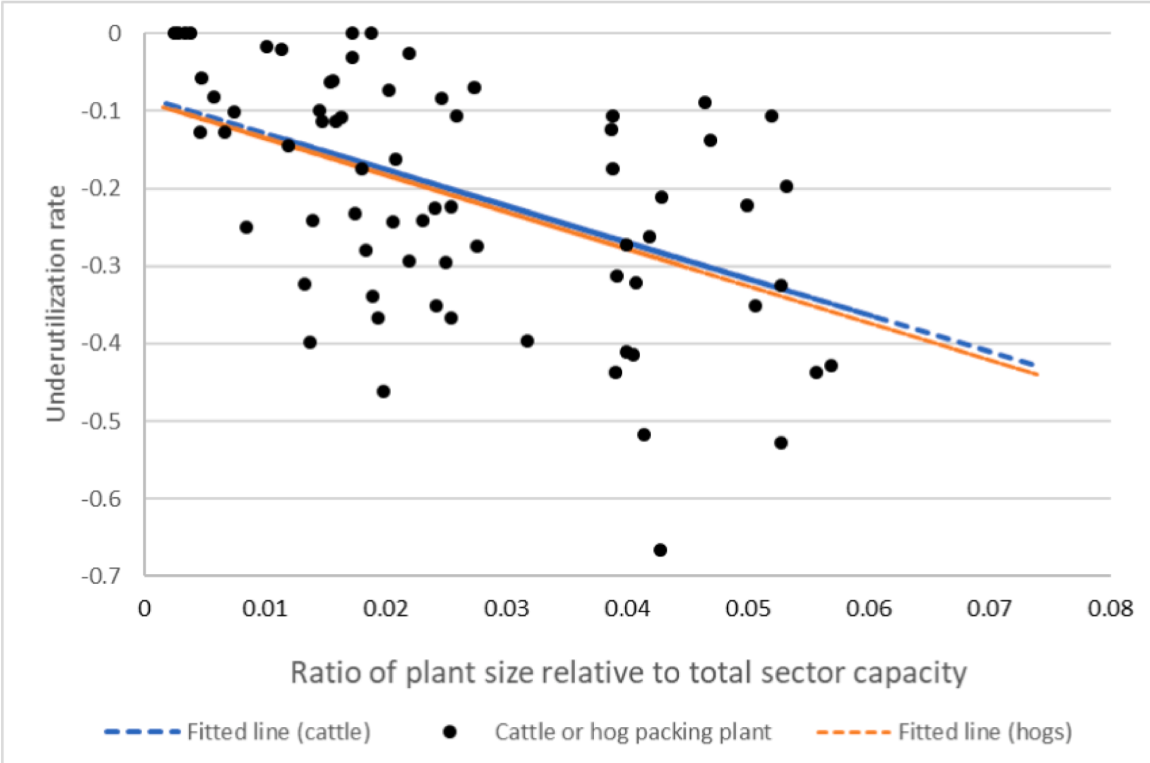

Fig. 5. Hog and cattle plant average underutilization rate relative to production capacity (April to May 2020) *Note*: Same as Fig. 4.

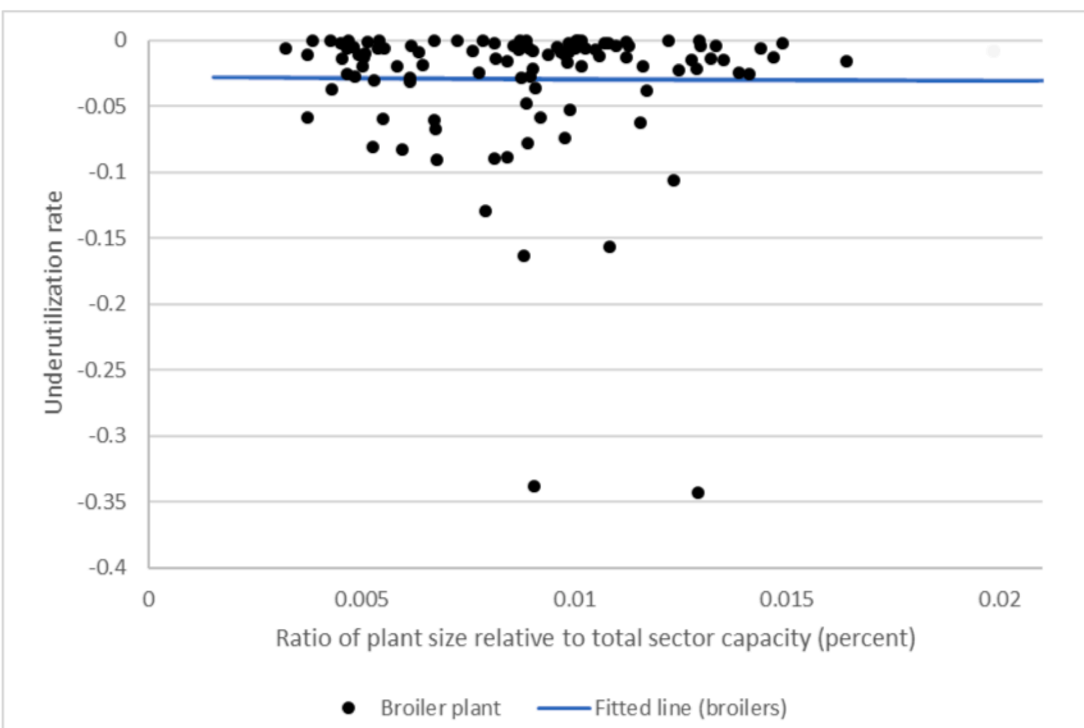

Fig. 6. Broiler plant average underutilization rate relative to production capacity (April 2020 to January 2022) *Note*: Same as Fig. 4.

econometrically-based structural break test. But first, we examine the breaks visually to make sure the results of the structural break tests are in the ballpark of reasonable values. A visual examination is facilitated by the production shock variable being mean reverting – looking at each individual plant, it is clear that plants make efforts to return the under-utilization rate to their desired optimal utilization rate, which tends to be around 5% under-utilization (i.e., plants will seek to operate at 95% of their physical production capacity). Fig. 8 presents the under-utilization rate across all plants in the analysis. The figure clearly shows that the major COVID slow-down and shut-downs occur in the

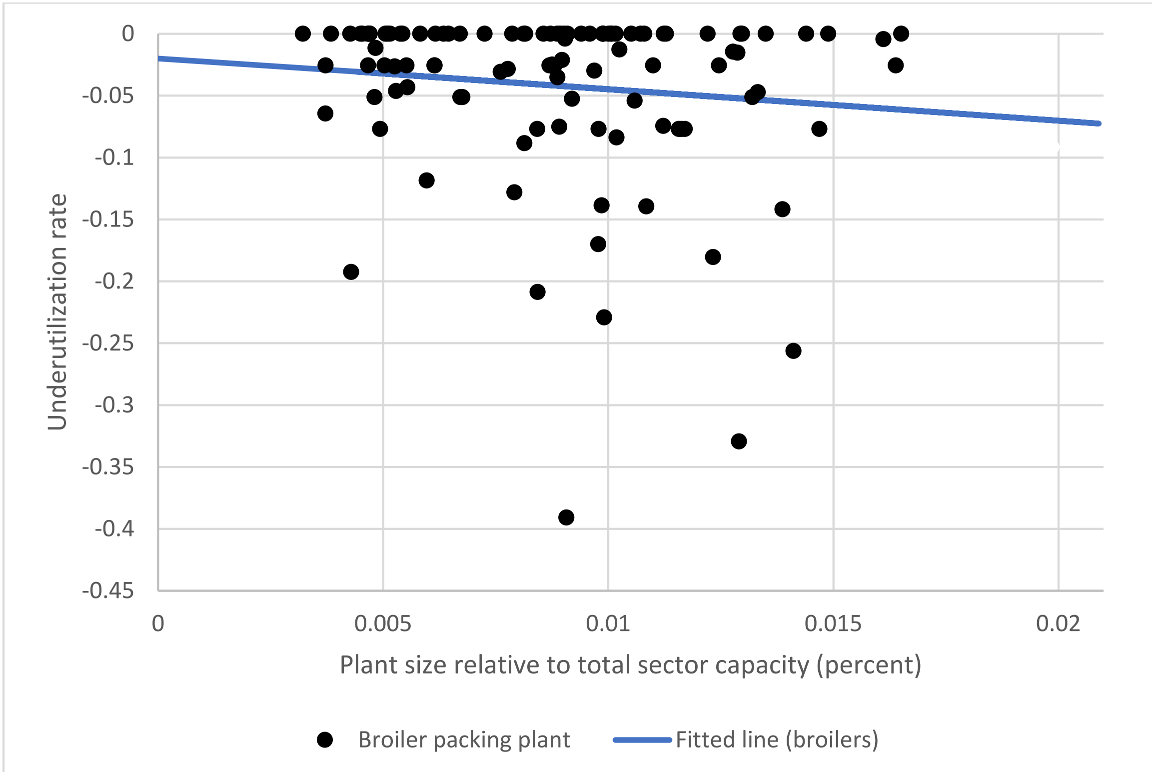

Fig. 7. Broiler plant average underutilization rate relative to production capacity (April 2020 to May 2020) *Note*: Same as Fig. 4.

Table 2
Descriptive statistics of key variables, cattle model.

Variable	Description	No. Obs.	Mean	SD
Plant capacity	Plant's long term capacity (daily head) as reported by the plant	15,014	3,106	1,704
Normal production	"Normal production" expected for the day as reported by the plant (head)	15,014	2,963	1,673
Current production	The day's total production (head) as reported by the plant	15,014	2,842	1,681
Underutilization	(current production − capacity)/capacity; daily measure	15,014	−0.091	0.152
Underperformance	(Current production − normal production)/normal production; daily measure	15,014	−0.038	0.152
SPX_index	Log of S&P500 index	15,014	8.250	0.153
PostJune2020	Dummy to differentiate the period after the heaviest plant shutdowns and slowdowns.	14,981	0.868	0.339
CovRtp	County-level seven day moving average of COVID-19 cases (source: Center for Disease Control)	14,981	33.698	43.770
Plant age	Age of plant (years)	14,981	29.576	6.111

Note: Other variables include fixed effects for state, month, and company in the regression tables), dummy variables for holiday periods, and a dummy variable indicating the invoking of the Defense Production Act (denoted as *DefensePA*).

April-June 2020 period with the structural break occurring around mid-June to mid-July. The spikes after that are for less plants and of shorter duration (Note that some of the 1 and 2 day spikes after mid-July 2020 will reflect floating holidays, but we cannot distinguish those from COVID shutdowns).

Next, we turn to using an econometric approach to determining the structural break. To do this for panel data, we use the *xtbreak* procedure (Ditzen, Karavias, and Westerlund, 2021) in STATA®, which allows the dynamic programming approach to finding structural breaks to minimize the sum of squared residuals from Bai and Perron (2003) to be applied to panel data. Applying this approach, we find the structural break occuring on 7/10/2020 (p-value significant at better than the 1% level of significance). This estimated break seems reasonable given that visual inspection of the data in Fig. 8 suggests a break somewhere between the end of May and early July 2020, with greatest amount of production shock occuring in April and May 2020.

Table 4 shows results for fully nested versions of regression (1) in Table 3, using the subsample of April 6 – July 10, 2020, post July 10–2020 and the whole time span. Comparison of the April 6 – July 10, 2020, post July 10–2020 shows that the impact of plant capacity on *underutilization* was three times higher and the impact of the county COVID infection rate on *underutilization* becomes insignificant after July 10, 2020. Most likely, changes in production practices at the plants lowered the impact of plant capacity and COVID on production shocks after the initial shock period.

The dependent variable in Table 5 is *underperformance*, which is an alternatives plant underutilization. The outcomes generally align with Table 3. However, the coefficient on plant capacity in the fractional logit regression in Table 5 is not significant, although the coefficient value is similar to that for OLS. This result suggests that plants' assessments of changes to the "normal production" variable reported by the plants and used to construct *underperformance* was not affected by plant size.

Table 3
Regressions using *Underutilization* of cattle plants as the dependent variable.

	Base				Quadratic terms			
	Linear		Fract. Logita		Linear		Fract. Logita	
Plant capacity	−0.021***	(0.002)	−0.029***	(0.002)	−0.042***	(0.012)	−0.065***	(0.009)
Plant capacity Sq.				0.003*	(0.002)	0.005***	(0.002)	
Year2021	0.016	(0.012)	0.009	(0.007)	0.015	(0.012)	0.003	(0.005)
SPX index	0.021	(0.043)	0.078	(0.061)	0.028	(0.043)	0.032	(0.022)
PostJune2020	0.078***	(0.020)	0.063*	(0.037)	0.075***	(0.020)	0.059	(0.039)
CovRtp	−0.648***	(0.068)	−0.406***	(0.071)	−0.919***	(0.100)	−0.652***	(0.102)
CovRtp Sq.					0.935**	(0.374)	0.780***	(0.222)
CovRtp time average[b]			−0.656	(0.975)			−1.626***	(0.504)
Plant age	−0.005***	(0.001)	−0.005***	(0.000)	−0.005***	(0.001)	−0.003***	(0.001)
Easter week	0.046***	(0.013)	0.028***	(0.007)	0.044***	(0.013)	0.025***	(0.007)
July 4 week	0.008*	(0.004)	0.015	(0.010)	0.008*	(0.004)	0.014	(0.010)
Thanksgiving w.	0.009*	(0.005)	0.010	(0.009)	0.009*	(0.005)	0.012	(0.009)
Xmas week	−0.003	(0.003)	0.002	(0.005)	−0.004	(0.003)	0.000	(0.004)
DefensePA	−0.006	(0.036)	−0.006	(0.012)	−0.004	(0.036)	−0.002	(0.012)
Constant	−0.213	(0.370)			−0.234	(0.370)		
Week day dummies	Yes		Yes		Yes		Yes	
Month dummies[c]	Yes		Yes		Yes		Yes	
Month by state dummies[d]	Yes		Yes		Yes		Yes	
Company dummies	Yes		Yes		Yes		Yes	
Scale factor			0.075				0.075	
Adj. R2.	0.314				0.315			
McFadden Pseudo R2			0.151				0.151	
LnL	9,968.7		−3,140.7		9,978.6		−3,138.1	
Obs.	14,981		14,981		14,981		14,981	

Note: To reduce leading zeros after the decimals, in these and subsequent regressions, *Plant_capacity* was divided by 1,000 and *CovRtp*, *PCapPreJune_COVIDRtp*, and the *COVIDRtp* variable by 10,000.
[a]For the fractional logit regressions, the coefficients on continuous variables are shown as the derivative of the function and as differences in the logistic PDFs for two different values for the discrete variables so as to allow comparison to the linear coefficient. The delta method was used to obtain the standard error of these coefficients. Their sign is reversed from the actual estimated value to facilitate comparison to the linear estimate given that the fractional logistic estimation assumes $0 \leq y \leq 1$, and thus required the dependent variable to be − *underutilization*.
[b] This coefficient is for the average across time for each plant *i* of $CovRtp_{it}$ and is used as part of the fixed effects estimation (Papke and Wooldridge, 2008). Standard errors are in parenthesis. [c]Plant age could not be included for reasons of collinearity in the OLS model with quadratic terms.
[c] These are dummies for each of the 12 months to capture seasonality at the monthly level.
[d] These are dummies for each state in the sample multiplied by dummies for each of the 22 months in the study, thus allowing state effects to vary over time. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4
Nested fractional logit regressions using *Underutilization* of cattle plants as the dependent variable.

	April 6–July 10 2020		Post July 10, 2020		Whole time span	
Plant capacity	−0.060***	(0.013)	−0.020***	(0.003)	−0.021**	(0.009)
SPX index	0.635**	(0.262)	−0.028*	(0.017)	0.149***	(0.050)
CovRTP	−1.577***	(0.157)	0.035	(0.050)	−0.429***	(0.075)
CovRtp time average[a]	5.215**	(2.393)	−0.995	(1.176)	−3.025	(3.144)
Plant age	−0.006***	(0.001)	−0.003***	(0.000)	−0.002*	(0.001)
Dummy variables	Yes		Yes		Yes	
Scale Factor	0.112		0.067		0.075	
McFadden Pseudo R^2	0.245		0.111		0.144	
LnL.	−621.9		−2,482.6		−3,166.1	
Obs.	2,243		12,771		15,014	

Note: the coefficients on continuous variables are shown as the derivative of the function and as differences in the logistic PDFs for two different values for the discrete variables. The delta method was used to obtain the standard error of these coefficients. Their sign is reversed from the actual estimated value in keeping with the previous tables. [a]This coefficient is for the average across time for each plant *i* of $CovRTP_t$ and is used as part of the fixed effects estimation using the approach in Papke and Wooldridge (2008). Dummy variables include weekday, state, and company fixed effects (time dummies excluded for consistency across the regressions). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5
Regressions using *underperformance* of cattle plants as the dependent variable.

	Linear		Fract. Logit[a]	
Plant capacity	−0.009***	(0.002)	−0.006	(0.005)
SPX index	0.014	(0.040)	0.005	(0.049)
PostJune2020	0.093***	(0.019)	0.097	(0.076)
CovRtp100	−0.710***	(0.069)	−0.262***	(0.030)
CovRtp100 bar			0.344**	(0.146)
Plant age	−0.004***	(0.001)	−0.130***	(0.003)
Easter week	0.049***	(0.013)	0.016***	(0.005)
July 4 week	0.006	(0.005)	0.022**	(0.010)
Thanksgiving w.	0.010*	(0.005)	0.017	(0.012)
Xmas week	−0.003	(0.003)	0.015	(0.010)
DefensePA	0.027	(0.036)	−0.006	(0.006)
Constant	−0.109	(0.338)		
Dummy variables	Yes		Yes	
Scale factor			0.0296	
Adj. R-sq.	0.2314			
McFadden Pseudo R2			0.352	
lnL	9,100		−1,447	
Obs.	14,981		14,981	

[a]The coefficients on continuous variables are shown as the derivative of the function and as differences in the logistic PDFs for two different values for the discrete variables so as to allow comparison to the linear coefficient. The delta method was used to obtain the standard error of these coefficients. Their sign is reversed from the actual estimated value to facilitate comparison to the linear estimate given that the fractional logit estimation assumes $0 \leq y \leq 1$, and thus required the dependent variable to be − *underperformance*. Dummy variables include weekday, state, month, year, and company fixed effects. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.3. *Plant size and county COVIID-19 infections – pooled time series-cross section regression analysis*

Saitone et al. (2021) found that the presence of a large beef plant increased COVID-19 infection rates by 110% relative to comparable counties without meatpacking plants. Here we examine the continuous relationship between plant size and COVID-19 infections, conditional on the presence of a plant in the county.

We aim to test whether the larger the plant capacity, and hence the larger the number of employees, the larger the potential COVID transmission. As with Table 4, in Table 6 we split the sample into April 6 – July 10, 2020 and post-July 10, 2020 periods. State, month, and company fixed effects are added as control variables, along with *plant age*. Note that *plant capacity* for all plants was unchanged over the span of the data, allowing little prospect for an endogenous relationship between it and *CovRtp*; plant capacity is pre-determined, having been set by some fixed investment made long before COVID. Also, that the estimation has fixed effects and is run at the daily level, which should alleviate much of the endogeneity issues.

The results show that the coefficient on *plant capacity* was positive and statistically significant on *CovRtp* in April 6 – July 10, 2020, and negative statistically significant afterwards. Pandemic protocols introduced by plants after the initial COVID wave seem to have significantly reduced the impact of plant size on community transmission, and even slightly reversed the impact. The elasticity of the {*CovRtp, plant capacity*} relationship was 1.21 over April 6 – July 10, 2020 and −0.096 afterwards. The decrease in county-level COVID infections as plant size increases after July 10, 2020 could be due to a combination of factors, including adoption of more stringent COVID-19 protocols by larger plants than smaller ones after July 10 and the initial infection surge prior to this date providing higher levels of resistance in the county later on. Plant age was not a factor in county level COVID-19 transmission rates during the initial surge but after July 10, 2020 was actually decreasing in plant age, albeit with an elasticity of −3.787. Perhaps older plants have more experienced management in dealing with labor issues. The R-squared for the April 6 – July 10, 2020 regression is 0.33 and increases to 0.66 afterwards.

While endogeneity cannot exist between COVID infection and plant capacity, at least over the span of this study, there could in principle be endogeneity between production and the COVID infection rate variable, but this is likely a complicated relationship. For instance, zero production suggests a shutdown, which might be expected to lead to a decrease in COVID rates in the community as long as transmissibility from workers staying at home to family members and then to others is less than the spread when transmission occurs at work.

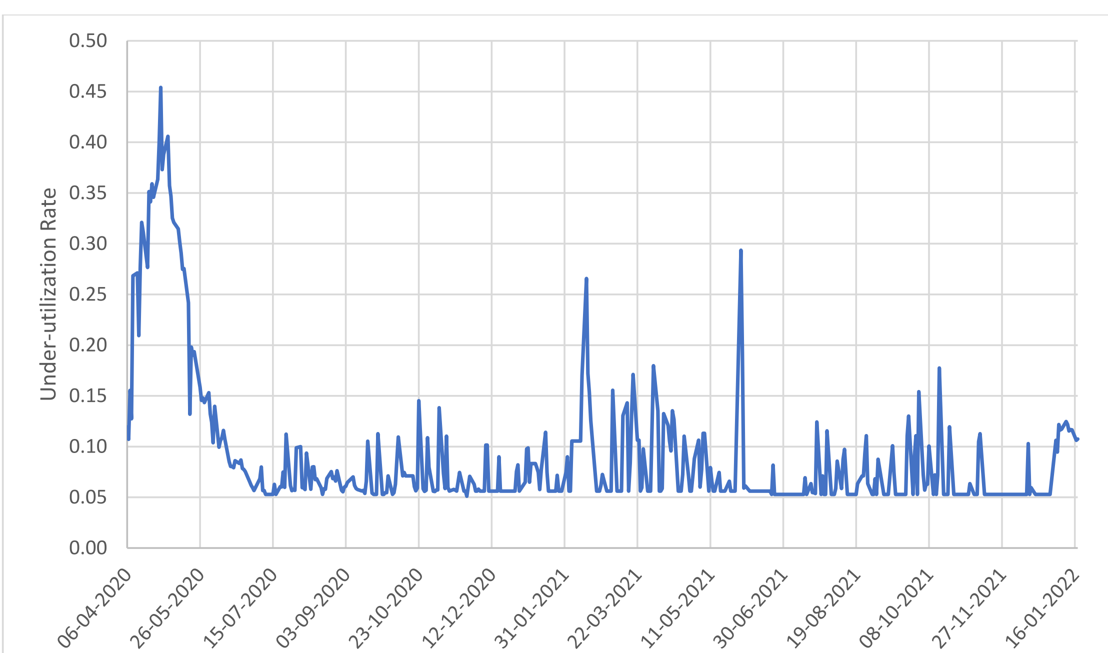

Fig. 8. Average Daily Under-utilization Rate for the Plants in the Analysis.

Table 6
Least squares regression results for county-level infection rates.

	April 6–July 10 2020		Post July 10 2020	
Plant capacity	0.010***	(0.001)	−0.001**	(0.000)
Plant age	0.000	(0.003)	−0.005***	(0.001)
Constant	−0.009***	(0.003)	0.188***	(0.024)
Dummy variables for fixed effects	Yes		Yes	
Adj R-sq.	0.330		0.655	
Obs.	2,243		12,771	

Note: Robust standard errors for the regressions are in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5. Policy implications

Our analysis addresses how plant disruptions caused by the COVID-19 outbreak varied by plant size and over time. It is clear from the analysis that while shocks were relatively large initially, and were increasing in plant size, they started dissipating within a couple of months, likely due to COVID-protocols undertaken by the plants. That production shocks were initially larger for large plants might motivate the question of how the resiliency of the meat packing sector could have differed if policy initiatives were undertaken to support construction of more small plants. The econometric results suggest that it is possible that small plants were nimbler in initially responding to COVID. However, beef plant size was significantly less important to maximizing utilization of processing capacity after the COVID initial surge.

Marginal and average processing costs per head decreases in plant processing capacity. For example, the data presented in Koontz (2021) implies an elasticity of average total costs of slaughter and fabrication with respect to processing capacity for a beef packing plant of −0.23. This result does suggest a trade-off between increasing cattle packer producer resiliency via increasing the number of smaller plants and lowering costs per unit. While economics cannot determine the optimum level of resilience versus efficiency without information on the relevant parameters of the social welfare function, the analysis in this paper provides the public and policymakers input into the political economy of this trade-off. The political economy space would have to decide how much it wants to reduce production uncertainty for perhaps relative short periods at the cost of less efficient production, and the potential need to support the plants in the face of excess capacity in normal periods.

While our results showed that production shocks were increasing in plant size during the initial surge of COVD-19, these result are contingent on the current distribution of plants by size. What might be the change in reaction of packing plants to COVID-19 if the industry structure was many small packing plants producing the same number of head instead of the current distribution with fewer but larger plants?[10] A distribution with many small plants to process the same number of head would collectively employ many more people than current large plants because small plants use significantly more labor per animal. In addition, if a 5,000 head per day plant did not exist, but was replaced with, say, 50 100 head per day plants, they would be located in the same general area as the large plant because that is where cattle are fed. The smaller production impacts we find at small plants could be likely the result of a lower concentration of the labor force and less illness. However, labor would not be less concentrated if more people were employed in the same area. While there would be fewer people in any single plant under a distribution with many smaller plants, the larger total group of plant workers would have more connections to others outside of plants. Hence, because of more total workers in area, having had more small plants with the same total capacity as the current distribution dominated by fewer larger plants might not necessarily have meant a smaller production shock in the first half of 2020.

Our analysis addresses the possible causes of plant disruptions from a largely physical standpoint and does not address the issue of market power, concentration, cattle producer profits, livestock prices or retail prices. Hadachek, Ma, and Sexton (2023) use a simulation model to show that adding smaller plants could improve resilience, but only if the market initially has high market power and if adding small plants is able to reduce the power.

Observed price patterns that are of concern—high retail prices and low livestock prices—are not themselves evidence of market power; Lusk, Tonsor, and Schultz (2021) find they are consistent with perfectly competitive models of the meat-packing sector. Some increase in the beef price spread due to the COVID-related packing plant shutdowns would be expected given that the processing bottleneck would lower prices received by the grower (live price or dressed weight). In the meantime, lower supply of processed beef would lead to increased box beef prices and retail prices, although the latter would have been affected by the food service disruptions as well. However, packing plant capacity rebounded by summer, and retail meat prices declined but remained 10% above pre-pandemic levels (Balagtas and Cooper, 2021). Azzam and Dhoubhadel (2022) do not find evidence of price/margin manipulation by cattle packers during the COVID-19 disruptions, either. Their result does not necessarily mean that price manipulation does not occur outside the context of the COVID-disruptions. Cattle markets may be thin in some regions at some points in time due to the share sold on spot markets being low relative to those sold via alternative marketing arrangements. It could be possible that lower transparency associated with thin markets led to price manipulations, echoing increased concentration in packing. For instance, Bolotova (2022) finds evidence consistent with the oligopoly and monopoly pricing in cattle over 2015–2019. Smaller packing plants under less concentrated ownership may lead to more competitive outcomes, and lower production shocks due to unexpected disruptions, at least in the short run, or they may not due to redistribution of labor issue noted above. Future research could weigh any benefits of smaller plants against potentially higher prices associated with lower economies of scale.

6. Conclusion

Our work capitalizes on a unique data set to analyze important questions about the impact of COVID-19 on meat processing and to contribute to the ongoing discussions surrounding this sector. Our finding of a greater pandemic impact on beef and pork processing as opposed to broilers is consistent with previous studies (e.g., Lusk et al. 2020), but we are also able to deeper analyze the impact using plant-level data as opposed to aggregate. An important contribution of this article is the finding of a larger underutilization rate for larger-sized beef and pork plants during Spring 2020, while no such relationship was found for broiler plants. In our panel analysis of beef packing plants, we found that higher COVID-19 infection rates in a county are associated with greater plant disruptions, but that plants appear to have been able to relatively quickly adjust to these disruptions. Our results suggest pandemic protocols by plants after the first COVID-19 wave significantly reduced the impact of plant size on community transmission.

Our results suggest there was a tradeoff between cattle plant size and utilization during the initial COVID surge in Spring and early summer of 2020. However, plant size was significantly less important concerning utilization after the initial surge. This leads to future questions about the potential implications of additional processing capacity and plant size. While small plants may be more resilient for short periods during extreme shocks similar to COVID-19 – at least under the current distribution of plants, firms will be concerned about plant profitability during

[10] We thank one of the anonymous reviewers for pointing out the key issues raised in this paragraph.

more normal times. Future work could consider the tradeoffs between plant size and profitability, noting data limitations on assessing profitability, as well as linking these to market competition.

CRediT authorship contribution statement

Joseph Cooper: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Vincent Breneman:** Data curation, Investigation, Resources, Software, Validation, Visualization, Writing – review & editing. **Meilin Ma:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Software, Writing – original draft, Writing – review & editing. **Jayson Lusk:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Writing – original draft, Writing – review & editing. **Joshua M. Maples:** Funding acquisition, Writing – review & editing. **Shawn Arita:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is funded under USDA cooperative agreement No. 58-0111-21-019.

References

Azzam, A., Dhoubhadel, S.P., 2022. COVID-19, beef price spreads, and market power. Agric. Resour. Econ. Rev. 47 (2), 462–476.
Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. J. Appl. Economet. 18 (1), 1–22.
Balagtas, J., Cooper, J., 2021. The impact of COVID-19 on United States meat and livestock markets. Choices, Quarter, p. 3.
Bina, J., Tonsor, G., Schulz, L., Hahn, W., 2022. Regional and plant-size impacts of COVID-19 on beef processing. Food Policy 108. Available online 14 March 2022.
Bolotova, Y., 2022. Competition issues in the U.S. beef industry. Appl. Econ. Perspect. 44 (3), 1340–1358.
Congress, 2021. "Coronavirus Infections and Deaths Among Meatpacking Workers at Top Five Companies Were Nearly Three Times Higher than Previous Estimates." Memorandum, Select Subcommittee on the Coronavirus Crisis. Task Force, House of Representatives, Congress of the United States, October 27, 2021.
Cowley, C. 2020. COVID-19 Disruptions in the U.S. Meat Supply Chain. Federal Reserve Bank of Kansas City, Main Street Views: Policy insights from the Kansas City Fed, July 31, 2021. https://www.kansascityfed.org/en/research/regionaleconomy/articles/covid-19-us-meat-supplychain.
Ditzen, J., Karavias, Y., Westerlund, J., 2021. Testing and Estimating Structural Breaks in Time Series and Panel Data in Stata. arXiv:2110.14550, [econ.EM].
Hadachek, J., Ma, M., Sexton, R., 2023. Market structure and resilience of food supply chains under extreme events. Am. J. Agric. Econ. 1–24 https://doi.org/10.1111/ajae.1239324.
Haley, M., 2020. U.S. Pork Processing Capacity Utilization Rebounds as COVID-19 Infections of Plant Labor Forces Recede. U.S. Department of Agriculture, Economic Research Service, Washington, DC. Chart of Note. https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=98682.
Herstein, J., Degarege, A., Stover, D., Austin, C., Schwedhelm, M., Lawler, J., Lowe, J., Ramos, A., Donahue, M., 2021. Characteristics of SARS-CoV-2 transmission among meat processing workers in Nebraska, USA, and effectiveness of risk mitigation measures. Emerg. Infect. Dis. 27 (4). https://wwwnc.cdc.gov/eid/article/27/4/20-4800_article.
Koontz, S.R., 2021. Another look at alternative marketing arrangement use by the cattle and beef industry. In: Fischer, Bart L., Outlaw, Joe L., Anderson, David P. (Eds.), The U.S. Beef Supply Chain: Issues and Challenges (Agriculture and Food Policy Center, Kansas City, 2021). https://www.afpc.tamu.edu/research/publications/710/cattle.pdf.
Krumel, T.P., Goodrich, C., 2022. Meatpacking working conditions and the spread of COVID-19. Appl. Econ. 1–24.
Lusk, J., Tonsor, G., Schultz, L., 2021. Beef and pork marketing margins and price spreads during COVID-19. Appl. Econ. Policy Perspect. 43 (1), 4–23.
Ma, M., Lusk, J.L., 2021. Concentration and resilience in the US meat supply chains. Natl. Bureau Econ. Rese. w29103.
Maples, J., 2021. Saturday Totals and Weekly Cattle Slaughter. Ohio BEEF Cattle Letter, May 12, 2021. https://u.osu.edu/beef/2021/05/12/saturday-totals-and-weekly-cattle-slaughter/.
Martinez, C., Maples, J., Benavidez, J., 2021. Beef cattle markets and COVID-19. Appl. Econ. Policy Perspect. 43 (1), 304–314.
NAMI, 2020. Meat Institute Issues Statement on OSHA Citation Related to COVID-19. North American Meat Institute, September 10, 2020. https://www.meatinstitute.org/ht/display/ReleaseDetails/i/179463/pid/287.
NAMI, 2021. COVID-19: Meat Worker Case Rates More Than 5 Times Lower than General Population. North American Meat Institute, March 2, 2021. https://www.meatinstitute.org/ht/display/ReleaseDetails/i/188764.
Padilla, S.L., MacLachlan, M.J., Vaiknoras, K., Schultz, L., 2023. Disasters, population trends, and their impact on the U.S. pork packing sector. Food Policy 118 (July), 102458.
Papke, L., Wooldridge, J., 1996. Econometric methods for fractional response variables with an application to 401 (K) plan participation rates. J. Appl. Economet. 11, 619–632.
Papke, L., Wooldridge, J., 2008. Panel data methods for fractional response variables with an application to test pass rates. J. Econ. 145, 121–133.
Saitone, T.L., Aleks Schaefer, K., Scheitrum, D.P., 2021. COVID-19 morbidity and mortality in US meatpacking counties. Food Policy 101, 102072.
The White House. 2022. The Biden-Harris Action Plan for a Fairer, More Competitive, and More Resilient Meat and Poultry Supply Chain. Fact Sheet, January 3, 2022. https://www.whitehouse.gov/briefing-room/statements-releases/2022/01/03/fact-sheet-the-biden-harris-action-plan-for-a-fairer-more-competitive-and-more-resilient-meat-and-poultry-supply-chain/.
Vaiknoras, Hahn, K.W., Padilla, S., Valcu-Lisman, A., Grossen, G., 2022. COVID-19 and the U.S. Meat and Poultry Supply Chains. COVID-19 Working Paper, AP-098, Economic Research Service, USDA, February 2022.
Waltenburg, M.A., Victoroff, T., Rose, C.E., Butterfield, M., Jervis, R.H., Fedak, K.M., Gabel, J.A., Feldpausch, A., Dunne, E.M., Austin, C., Ahmed, F.S., Tubach, S., Rhea, C., Krueger, A., Crum, D.A., Vostok, J., Moore, M.J., Turabelidze, G., Stover, D., Donahue, M., Edge, K., Gutierrez, B., Kline, K.E., Martz, N., Rajotte, J.C., Julian, E., Diedhiou, A., Radcliffe, R., Clayton, J.L., Ortbahn, D., Cummins, J., Barbeau, B., Murphy, J., Darby, B., Graff, N.R., Dostal, T.K.H., Pray, I.W., Tillman, C., Dittrich, M. M., Burns-Grant, G., Lee, S., Spieckerman, A., Iqbal, K., Griffing, S.M., Lawson, A., Mainzer, H.M., Bealle, A.E., Edding, E., Arnold, K.E., Rodriguez, T., Merkle, S., Pettrone, K., Schlanger, K., LaBar, K., Hendricks, K., Lasry, A., Krishnasamy, V., Walke, H.T., Rose, D.A., Honein, M.A., 2020. Update: COVID-19 Among Workers in Meat and Poultry Processing Facilities—United States, April–May 2020. Morbidity and Mortality Weekly Report: 887-892, U.S. Department of Health and Human Services, Centers for Disease Control and Prevention.