Livestock plants and COVID-19 transmission

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Policy responses to the COVID-19 outbreak must strike a balance between maintaining essential supply chains and limiting the spread of the virus. Our results indicate a strong positive relationship between livestock-processing plants and local community transmission of COVID-19, suggesting that these plants may act as transmission vectors into the surrounding population and accelerate the spread of the virus beyond what would be predicted solely by population risk characteristics. We estimate the total excess COVID-19 cases and deaths associated with proximity to livestock plants to be 236,000 to 310,000 (6 to 8% of all US cases) and 4,300 to 5,200 (3 to 4% of all US deaths), respectively, as of July 21, 2020, with the vast majority likely related to community spread outside these plants. The association is found primarily among large processing facilities and large meatpacking companies. In addition, we find evidence that plant closures attenuated county-wide cases and that plants that received permission from the US Department of Agriculture to increase their production-line speeds saw more county-wide cases. Ensuring both public health and robust essential supply chains may require an increase in meatpacking oversight and potentially a shift toward more decentralized, smaller-scale meat production.

COVID-19 | supply chains | livestock | agriculture | public health

Among the many challenges posed by the COVID-19 outbreak, maintaining essential supply chains while mitigating community spread of the virus is vital to society. Using county-level data as of July 21, 2020, we test the relationship between one such type of essential activity, livestock processing, and the local incidence of COVID-19 cases. We find that the presence of a slaughtering plant in a county is associated with four to six additional COVID-19 cases per thousand, or a 51 to 75% increase from the baseline rate. We also find an increase in the death rate by 0.07 to 0.1 deaths per thousand people, or 37 to 50% over the baseline rate. Our estimates imply that excess COVID-19 infections and deaths related to livestock plants are 236,000 to 310,000 (6 to 8% of all US cases) and 4,300 to 5,200 (3 to 4% of all US deaths), respectively, with the vast majority occurring among people *not* working at livestock plants.

We further find the temporary closure of high-risk plants to be followed by lower rates of COVID-19 case growth. We also find that smaller, decentralized facilities do not appear to contribute to transmission and that plants that received permission from the US Department of Agriculture (USDA) to increase their production-line speeds saw more county-wide cases. Our associations hold after controlling for population risk factors and other potential confounders, such as testing rates. Although lacking a natural experiment to cement causality, we employ a combination of empirical tools—including an event study, instrumental variables (IVs), and matching—to support our findings.

The centrality of livestock processing to local economies and national food supplies implies that mitigating disease spread through this channel may take an economic toll. Understanding the public health risk posed by livestock processing is essential for assessing potential impacts of policy action. However, generating case data attributable to livestock plants is challenging: Contact tracing in the United States is decentralized and sporadic, and there may be incentives for companies and government bodies to obscure case reporting (1–5). Our study represents an attempt to address this gap in knowledge.

Heterogeneity in COVID-19 Patterns

The disease burden of COVID-19 is not uniformly distributed across the global population. Certain conditions appear to influence the degree to which people spread the virus. Some contexts and social behaviors are believed to lead to superspreading events that disproportionately affect local populations (6, 7). Previous studies have explored links between the incidence of COVID-19 cases and a range of demographic and environmental factors, such as age, occupation, income, race, intergenerational mixing, temperature, and humidity (8–13). Social, commercial, and industrial activities are also believed to affect transmission, for which reason countries worldwide have implemented a range of economic and social-distancing measures (8, 14–20). In the United States, some industries are exempted from shelter-in-place orders and have remained operational due to their necessity to satisfy basic societal needs (21). We investigate the relationship between transmission and one such activity, livestock processing.

COVID-19 and Livestock Plants

The livestock- and poultry-processing industry is an essential component of the global food supply chain. In the United States, it is a large industry, employing 500,000 people. It is also highly concentrated: The largest four companies in beef, pork, and poultry processing capture 55 to 85% of their respective markets (22–27). This degree of concentration stands in contrast to the European Union (EU), for example, where the top 15 meat companies represent 28% of EU meat production (28).

Significance

The COVID-19 pandemic is a public health and economic crisis in which policymakers face tradeoffs between maintaining essential economic activities and mitigating disease spread. Our study suggests that, among essential industries, livestock processing poses a particular public health risk extending far beyond meatpacking companies and their employees. We estimate livestock plants to be associated with 236,000 to 310,000 COVID-19 cases (6 to 8% of total) and 4,300 to 5,200 deaths (3 to 4% of total) as of July 21. We also illustrate potential contributions of plant size, industrial concentration, plant shutdowns, and policy actions to this phenomenon. These results motivate investigation into supply chains, operating procedures, and labor relations within the meatpacking industry.

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Over the decades, the livestock- and poultry-processing industry in the United States has consolidated its operations into fewer, larger plants, in which meat production per plant has increased threefold since 1976 (29, 30). Today, 12 plants produce over 50% of the country's beef, and 12 others, similarly, produce over 50% of the country's pork (30, 31). Early in the COVID-19 pandemic, livestock-processing plants worldwide experienced spikes in infections, facing shutdowns that disrupted meat and dairy supplies (32–35). In the United States, reports of COVID-19 spreading within the livestock-processing industry led to increased attention and updated safety guidance by the Centers for Disease Control and Prevention (CDC) (22). Several plants were forced to shut down until, among other factors, a federal executive order invoked the status of livestock processing as "critical infrastructure" for national security and mandated that these plants remain open (36, 37).

Work routines in livestock processing have several characteristics that make plants susceptible to local outbreaks of respiratory viruses. The CDC includes the following among potential risk factors: long work shifts in close proximity to coworkers, difficulty in maintaining proper face covering due to physical demands, and shared transportation among workers (22). Previous research has proposed occupational exposure to livestock animals as a driver of viral spread, although an experimental study did not find pigs or chickens to be susceptible to the SARS-CoV-2 virus associated with COVID-19 (38–41). Increases in production-line speeds due to technological enhancements as well as policy changes have also been hypothesized to exacerbate COVID-19 transmission (5, 42). Among those we investigate are USDA waivers on poultry-production line-speed limits for plants with strong commercial production practices and microbial control (43).*

The indoor climate of livestock facilities may increase transmission risk. To preserve meat after slaughter, processing areas are maintained at 0 to 12 °C (44), and such low temperatures have been linked to increased COVID-19 risk (45, 46). Though these rooms are kept at 90 to 95% relative humidity to prevent meat from drying and losing weight, the low absolute humidity at near-freezing temperatures may encourage the transmission of airborne viruses such as influenza (47–49). Moreover, studies have suggested that industrial climate control systems used to cool and ventilate meat processing facilities may further the spread of pathogenic bioaerosols, a proposed COVID-19 transmission route (46, 50–53).

Workers' socioeconomic status and labor practices may also contribute to infection and transmission. Among front-line meat-processing workers in the United States, 45% are categorized as low income, 80% are people of color, and 52% are immigrants, many of whom are undocumented and lack ready access to healthcare and other worker protections that could facilitate COVID-19 prevention and treatment (54–56). In addition, employees at these facilities may face incentives to continue working even while sick through company policies on medical leave and attendance bonuses (5, 22, 57). In addition, through consolidation over the decades, the meatpacking industry has potentially increased its monopsonistic power over labor markets, which has been linked to greater work hazards (58–60).

Results

We find a strong relationship between proximity of livestock plants and the incidence of COVID-19 over time. Fig. 1 plots average COVID-19 case and death rates over time by whether there is a large livestock facility in a given county relative to rates in counties at varying distances from a plant. In both cases, we see an increasing divergence in outcomes beginning in early April based on livestock-plant proximity.

Fig. 1 does not account for county-level differences in terms of density and demographics. In Table 1, we estimate the relationship between livestock plants and COVID-19 incidence as of July 21, 2020, using regression models that control for potential confounding variables, including county-level measures of income; population density and its square; the timing of the first case; the proportions of elderly people, uninsured people, front-line workers, and people using public transportation; racial and ethnic characteristics; average household size; local freight traffic; and populations of nursing homes and prisons. We find that livestock plants are associated with an increase in COVID-19 cases by approximately four per thousand people, representing a 51% increase over the July 21 baseline rate of eight per thousand. Likewise, death rates increase by 0.07 per thousand, or 37% over the county baseline of 0.2 deaths per thousand. The results are robust both nationally and when only considering variation within states after including state fixed effects. We also use an alternate specification with a binary measure of whether a county has one or more livestock plants. Such counties are associated with six additional cases per thousand, or a 75% increase over the baseline, as well as 0.1 additional deaths per thousand, or 50% over the baseline county death rate.† In addition, COVID-19 appears to arrive earlier in counties with livestock plants (*SI Appendix*, Table S2).

Heterogeneity by Facility Type, Size, Operations, and Company. We now present potential characteristics of livestock facilities that might contribute to these observed relationships with the COVID-19 case and death rate.

Facility type. We first looked at the relationship between reported cases and the type of animal slaughtered or processed. We found that beef, pork, and poultry plants each show a significant relationship with COVID-19 cases and deaths, with pork plants showing the greatest measured magnitude of the three in cases and beef plants showing the greatest magnitude in deaths (*SI Appendix*, Table S3). As seen in the map in Fig. 2, pork and beef plants are well distributed throughout the United States, and, although, poultry plants are relatively concentrated in the southeastern United States, they are found across 10 states. Overall, the wide geographic distribution of facilities by type mitigates concerns of this being a regional phenomenon.

Facility size. We next investigated whether there are differential relationships with COVID-19 transmission based on the size of processing facilities. Livestock facility data were gathered from the USDA's Food Safety and Inspection Service (FSIS). *SI Appendix*, Table S4 categorizes beef, pork, and poultry plants by order of magnitude based on the pounds per month processed: large (category 5; over 10 million), medium (category 4; over 1 million), and small (category 3; over 100,000 and under 1 million). Each size category was sufficiently represented, with 349 small plants, 126 medium plants, and 225 large plants. Very small plants (categories 1 and 2), which are often niche providers, were excluded.‡

*The CEOs of Wayne Farms and Tyson Foods—both granted waivers in April 2020—are, respectively, chairman of the National Chicken Council (the body that initially lobbied for the line speed waivers) and a public advocate for the poultry industry, buying full-page newspaper ads in April stating that the food supply chain was "broken."

†In line with the literature, we find COVID-19 incidence to be strongly associated with population density, average household size, the timing of the first confirmed case, and the proportion of a county's population who are public-transit commuters, elderly, Black, Hispanic, in a nursing home, uninsured, or institutionalized (*SI Appendix*, Table S1).

‡In our main analyses, we included category 4 and 5 pork and beef facilities and category 5 poultry facilities (which comprise 57% of total poultry plants); see *Materials and Methods* for a full discussion.

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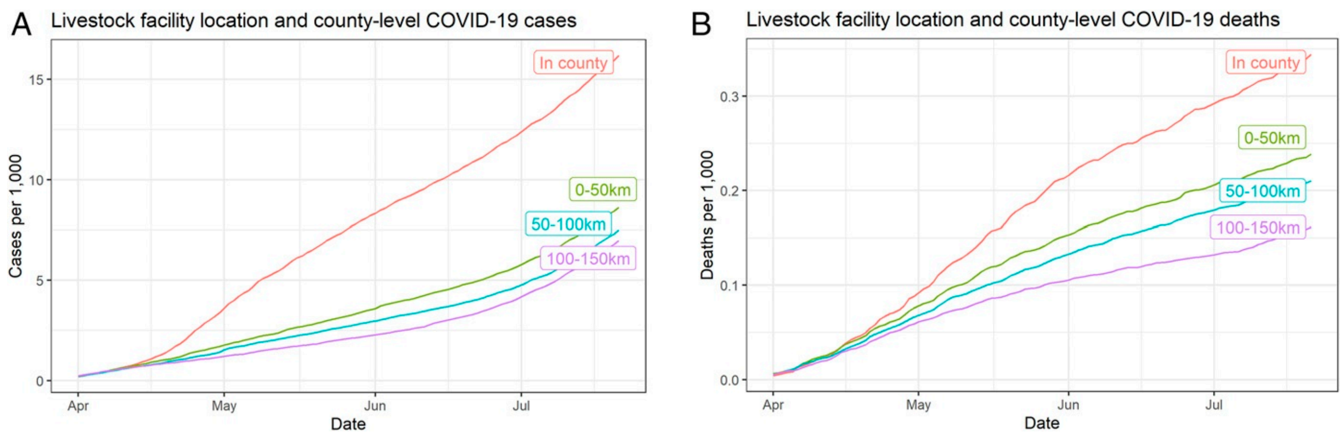

Fig. 1. Mean county-level COVID-19 cases per thousand (*A*) and deaths per thousand (*B*) over time based on proximity to a livestock facility. The band "0–50 km" excludes the county itself. Counties are categorized into nonoverlapping, single categories based on the nearest facility (e.g., if a county contains a livestock facility and is within 50 km of another facility outside the county, the county is coded "In county" and not "0–50 km"). A visualization map is included in *SI Appendix*, Fig. S1.

We found the relationship between livestock plants and COVID-19 transmission to be most pronounced among the largest plants, whose presence in a county is associated with a 35% higher COVID-19 case rate relative to the average coefficient for livestock plants shown in Table 1. Small and medium-sized plants were generally not found to have significant relationships with local COVID-19 transmission, suggesting that the scale of production is an important variable for industry leaders and policymakers to consider.

Production line speeds. We next examined whether there is a relationship between local COVID-19 transmission and plant-operating procedures. We collected data on whether a poultry plant had been granted a waiver from the USDA permitting production-line processing speeds of 175 birds per minute, up from the statutory limit of 140. Waivers were first issued to 20 poultry plants in 2012 as part of a pilot study to test self-monitoring of safety. It was then expanded in September 2018 to allow all poultry plants the opportunity to apply for these waivers. A faster production line can result in both workers locating in greater proximity to one another and increased difficulty in maintaining personal protective equipment and thus could contribute to conditions that increase the likelihood of viral transmission.

Of the 120 poultry plants in our sample, 48 plants currently have waivers, 16 of which were issued in 2020.[§] An analysis of the relationship between line speed waivers and local COVID-19 incidence suggests, though with less precise estimates, that waivers predict increases in county-level case rates double those in counties with nonwaiver poultry plants (*SI Appendix*, Table S5). Among plants issued a waiver in 2020, the relationship is even greater in magnitude. This finding suggests a potential pathway between a livestock plant's operating procedures and COVID-19 transmission.

Facility operator. We next looked at differential relationships with COVID-19 by company. The relationship between local COVID-19 incidence and medium and large plants (FSIS categories 4 or 5) owned or operated by some of the largest US processors (National Beef, JBS, Tyson, Cargill, and Smithfield) and their subsidiaries is presented in *SI Appendix*, Table S6. These magnitudes can be visualized in Fig. 3: The strongest relationship is found with National Beef, whose indicated relationship with COVID-19 case rates is approximately five times greater in magnitude than that of other livestock facilities. However, all of the large companies appear to have larger coefficients than the baseline. Aside from Smithfield, the relationship with deaths is positive, albeit less significant, which may be due to small sample size.[¶]

Behavioral change. If livestock facilities are driving higher COVID-19 incidence, and if livestock processing is an essential industry, we would expect people in livestock-plant counties to work more compared to those in nonlivestock counties in response to COVID-related lockdowns. To this end, we employed county-level mobility data made available by Google for COVID-19 researchers. We constructed a baseline measure of average time-use change before and after March 13, 2020, the date the United States declared a national disaster in relation to COVID-19 and shortly after the World Health Organization declared COVID-19 a pandemic.

We then examined how the presence of livestock plants varied with time spent working and engaging in shopping and recreation. We controlled for the same demographic and location-based covariates as in other models. We found that the presence of livestock plants is strongly associated with more time spent at work (*SI Appendix*, Table S7). This association is relative to the baseline behavior change across all other counties, indicating that people in livestock-plant counties are working more (or cutting back on work less) than people in other counties. Meanwhile, there is a lesser and imprecise relationship with retail and recreation activities, which may contribute to viral spread. This supports the notion that livestock plants, rather than unrelated changes in behavior in these same counties, are the more likely vehicle of COVID-19 transmission.[‖]

Plant shutdowns. Many livestock plants were temporarily shut down to halt the spread of COVID-19. In such cases, we would expect the dynamics of caseloads and deaths over time to vary negatively with the timing of shutdown, after a lag. Were confounders instead driving our results, they would have to follow

[§]Among counties with poultry plants, those with and without waivers appear similar in their average characteristics, reducing waiver-selection concerns. The exception is that waiver counties have lower proportions of Black residents and prison populations, factors associated with increased COVID-19 risk.

[¶]In our collected sample, the number of facilities per company varies: National Beef has only seven plants in seven counties, whereas Tyson Foods has 80 plants across 69 counties. The other companies fall somewhere in between.

[‖]It is possible that additional time spent working, and thus out of the house, may explain some of the additional time spent on retail activities (e.g., gas stations or workday meals).

Table 1. Livestock facilities and county-level COVID-19 incidence

	COVID-19 incidence per 1,000 as of July 21, 2020					
	Case rate			Death rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Livestock facility	4.49***	4.07***	5.98***	0.07***	0.07***	0.10***
	(0.88)	(0.80)	(1.14)	(0.02)	(0.02)	(0.02)
Plant count	Level	Level	Binary	Level	Level	Binary
Controls	X	X	X	X	X	X
State FE		X	X		X	X
Observations	3,032	3,032	3,032	3,032	3,032	3,032
R^2	0.36	0.45	0.46	0.27	0.42	0.42

Regression model with cross-sectional county data. Dependent variable is COVID-19 cases (models 1 to 3) and deaths (models 4 to 6) per thousand. Livestock facility level is the sum of beef, pork, and poultry plants in the county. Livestock facility binary denotes a binary variable representing whether a county has at least one livestock plant. Controls include income per capita (log), density (population per built-up land area) and density squared, the number of freight miles traveled, and timing of first case (index of Julian day of first confirmed case), as well as proportions of the county population over the age of 70, Black, Hispanic, public-transit commuters, uninsured, frontline workers, or in nursing homes or prisons. State-level fixed effects (FE) are included in models 2, 3, 5, and 6. SEs are clustered at the state level.
$^{***}P < 0.01$.

the timing of the plant shutdowns as well. This helps argue against purely static confounders, such as highway connectedness or fraction of the population that is Hispanic.

Using a dataset tracking whether and when livestock plants closed, Fig. 4 presents an event study comparing the change in weekly COVID-19 case rates before and after closure, averaged across counties with plants that closed and counties with plants with no evidence of closure. Among livestock plants in our sample, we have the dates of closures that occurred in 26 counties, or 10% of counties with plants. The mean closure time was 9 d. Some closed for a day or two for cleaning and disinfection, while others closed for longer periods while revising their operating procedures and monitoring staff. On the other hand, many plants remained open due to a perceived lack of risk, while others remained open despite significant local outbreaks.

In this event study, we examined case growth (weekly log difference), following the structure of a previous analysis (61), as well as change in case rates. In addition, we performed prepolicy matching across the two groups based on percent case growth in the 2 wk prior to shutdown. In doing so, we selected the top quartile of growth rates among the 233 counties with livestock plants that did not have a plant shutdown. We took this step to maximize comparability between the two groups, as we observed that preclosure growth in cases was, on the whole, greater in plants that closed (*SI Appendix*, Fig. S2).

Coefficients are plotted from a panel regression, where counties (categorized as either having or not having a plant closure) are interacted with the weekly event index, both in terms of percent growth in cases (Fig. 4 *A* and *C*) and the change in case rates per 1,000 (Fig. 4 *B* and *D*). This model controls for state-level social distancing and stay-at-home policy and includes a fixed effect for each county, thereby isolating within-county variation in timing (among counties with plant closures).

Fig. 4 shows that plant closures occurred in counties experiencing high growth in COVID-19 cases, as might be expected. Within 1 wk of closure, however, the growth rate in shutdown counties reverted to the prepolicy growth rate from a higher peak, compared to nonshutdown counties in the same time. By week 2, growth rates between the two categories, highly divergent in week 1, were roughly equal. By weeks 3 to 4, average growth rates in shutdown counties were, in fact, lower than even counties without plants. This lag structure for cases aligns with the fact that COVID-19 incubation periods may last for up to 14 d (62).

The lower sustained COVID-19 growth rate postclosure suggests that plant closures have some relationship with COVID-19 transmission, which, in turn, suggests some relationship between plant-level activity and community disease spread within the county. Given that the average closing period was only 9 d, it is unclear whether the plant closures themselves reduced COVID-19 transmission rates, or whether closures resulted in plants taking more COVID-19 precautions (e.g., implementing enhanced safety protocols). It is also true that locales initially experiencing growth spikes will likely revert to average growth rates over time. However, the speed with which growth rates rose and fell in shutdown counties suggests that some closure-related mechanism is likely at play. And while shutdown counties have higher cumulative COVID-19 caseloads on average, this is likely because closures occurred too late to suppress community spread outside of these plants.

Robustness.

COVID-19 testing. Next, we address concerns that these results primarily reflect differences in testing. Places with more testing tend to have more confirmed COVID-19 cases than places with less testing (mechanically). There does not appear to be a national database on county-level testing, so we compiled data from 31 states that have livestock facilities and testing data at the county level. Table 2 shows that, while testing is positively associated with COVID-19 incidence, the relationship to livestock facilities remains large and significant. In a second specification, we added the positivity rate (total cases divided by total tests) as a further control. The magnitude of the livestock coefficients are of a similar magnitude to those in the baseline model in Table 1. However, these estimates are not directly comparable because of the smaller sample size of counties with testing data (1,773 counties across the 31 states).

Manufacturing activity. It is possible that a certain type of work similar to livestock processing—but not livestock processing itself—is driving the spread of COVID-19. To test this, we controlled for the county-level number of manufacturing establishments and share of income from manufacturing. We found that the relationship between livestock plants and COVID-19 incidence remained largely stable, meaning that it is not explained by a correlation with manufacturing (*SI Appendix*, Table S8). While there is no obvious relationship with number of manufacturing establishments, the coefficient for manufacturing share of income is positive and statistically significant, implying that

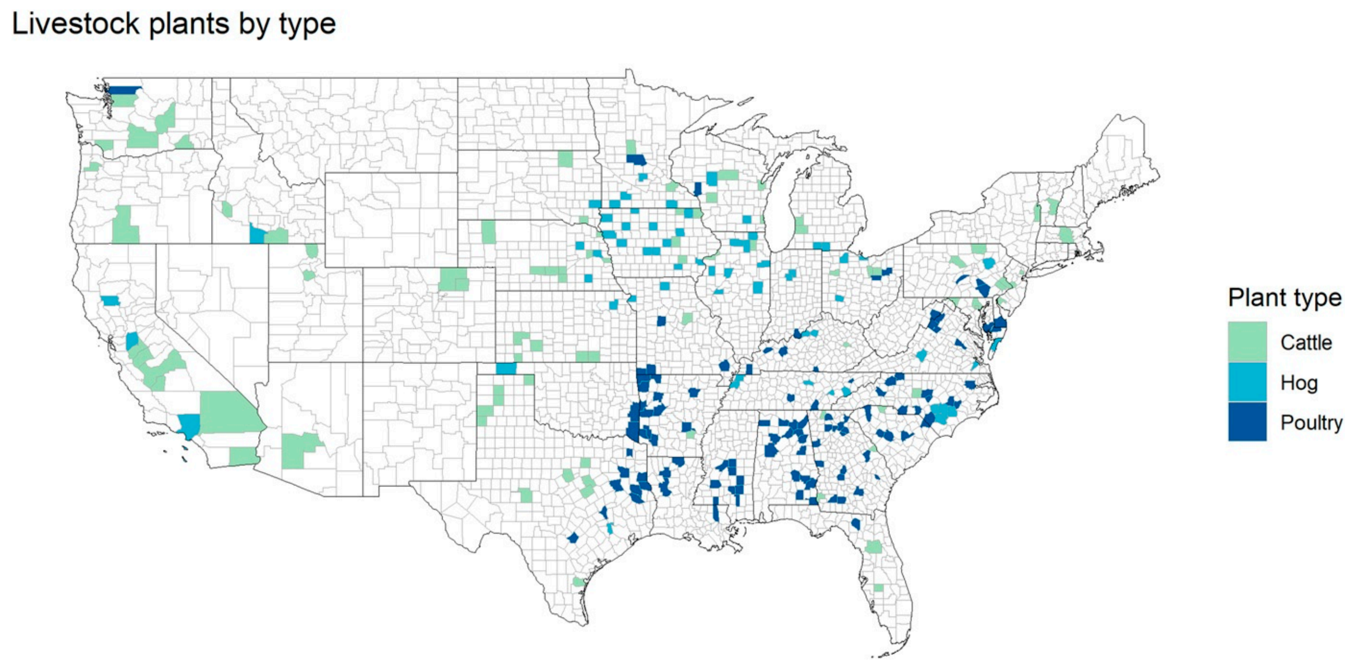

Fig. 2. Shaded counties contain at least one beef or pork facility categorized by USDA FSIS as processing more than 1 million pounds per month (categories 4 and 5) or at least one poultry facility categorized as processing more than 10 million pounds per month (category 5).

manufacturing may be associated with higher COVID-19 incidence. Such a relationship is plausible given that, like livestock processing, employees in the manufacturing sector may work in close proximity and that many manufacturing activities are considered essential to supply chains.

Dropping counties distant from livestock plants. Another potential concern is that counties very far from livestock plants have lower population densities and different demographic makeups than counties nearer these plants. Correspondingly, there is a risk that incorporating these counties into our analysis may introduce bias into our livestock-plant estimates. An analysis omitting counties more than 100 km from a county with a livestock plant showed a relationship with livestock facilities greater in magnitude than the base specification, indicating that our findings are robust to this risk and, perhaps, somewhat conservative (*SI Appendix*, Table S9).

Dependent-variable transformations. To address concerns about a skewed outcome variable, we employed the natural log and inverse hyperbolic sine of the dependent variable and found a consistently positive, but smaller-magnitude, relationship between livestock plants and increased COVID-19 case and death rates (*SI Appendix*, Table S10).

Alternative Statistical Approaches to Confounding. Above, we have shown the robustness of multivariate regression results to various confounders—demographic, geographic, and behavioral—and sample-selection criteria. Additionally, we have shown that the dynamics over time of COVID-19 cases and deaths vary with the timing of livestock-plant shutdowns.

Here, we present results of additional statistical methods used to explore the relationship between livestock plants and COVID-19 cases and deaths in the cross-section. The methods we used to help address potential bias and endogeneity concerns are IV analysis, propensity-score matching, and nearest-neighbor matching. We note that the 259 counties in our sample with livestock plants differ in important ways from those without plants. We constructed a balance table comparing counties with and without livestock plants (*SI Appendix*, Table S11). Counties with plants have higher population density, a lower proportion of elderly people, higher proportions of Black and Hispanic people, and larger household sizes. Income levels, by contrast, are similar. Each particular statistical method adjusts for these baseline differences in different ways. To preview, we find the observed relationship with COVID-19 incidence to be robust to all three approaches.

Instrumental variables. First, we employed an IV approach using historical livestock agricultural production data. The selection of this instrument was motivated by meat processors' need to minimize costs of transporting livestock supply when selecting the location of plants. In the first stage, we regressed the current number of livestock plants in each county on the county's livestock-production value in 1959 in terms of animals sold, as derived from the USDA census. Note that this only includes agricultural operations, and not livestock processing. We believe that this is a strong instrument, given that most of the interstate highway system was constructed during the 1960s, most currently operating livestock processing plants were built in the 1970s or later, and livestock agricultural operations in 1959 appear unlikely to affect current public health outcomes.

In the second stage, we regressed COVID-19 incidence on this predicted value of livestock plants as well as the other covariates in the primary specification. The first stage in the IV analysis, presented in *SI Appendix*, Table S12, shows that the instrument is highly relevant with the F-statistic far above Stock and Yogo's (63) 10% maximal bias threshold. The overall IV results in Table 3 show the relationship between livestock facilities and COVID-19 case and death rates to be even stronger for each outcome, except the within-state death rate, which is of comparable magnitude but less precisely estimated. We note that the IV approach restricts identifying variation to that attributable to livestock agriculture proximity, thereby reducing statistical power.

Propensity-score and nearest-neighbor matching. For both propensity-score matching and nearest-neighbor matching, we constructed comparable subsamples of our dataset with and without livestock facilities to estimate an effect of having these

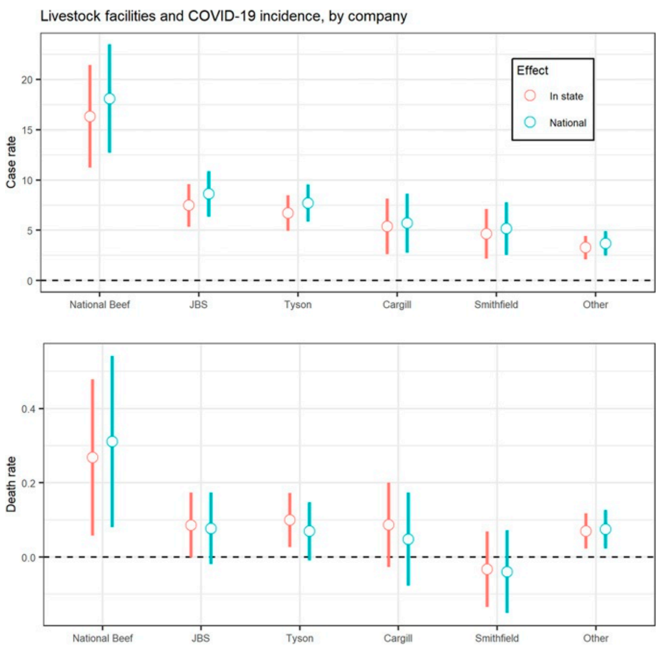

Fig. 3. Relationship between COVID-19 cases and livestock plants owned or operated by large meatpacking companies. Coefficients are firm fixed-effect coefficients plotted from *SI Appendix*, Table S6. Error bars represent 95% CIs.

livestock facilities among otherwise similar counties on COVID-19 cases and deaths.

For propensity-score matching, we first predicted the probability that a county has at least one livestock facility (binary value) using a binomial regression that includes all of the covariates from our primary model specification in Table 1, as well as their quadratic terms to increase model flexibility. We then confirmed that observations were relatively balanced across covariates within each propensity-score quartile (*SI Appendix*, Table S13. This suggests that the propensity score is, indeed, balancing the multidimensional covariates. In a second step, we used this predicted probability (i.e., the propensity score) as a control in a regression of COVID-19 incidence on livestock plants. The idea is that the propensity score helps account for bias in the location of livestock plants.

For nearest-neighbor matching, we used the *MatchIt* package in R to restrict the sample to similar treated and control groups. The matching occurred by using a nearest-neighbor algorithm based on predicting the livestock binary variable with the covariates in our primary specification. To ensure an adequate sample size, we allowed the algorithm to match two nonplant counties to every one county with a livestock plant. We found the resulting 774 county subsample to be well balanced (*SI Appendix*, Table S14).[**] *SI Appendix*, Table S15 consolidates the results and includes outputs from Table 1 for reference. In this analysis, coefficients for both case and death rates remain of a similar magnitude and level of significance.

Community spread beyond livestock plants. COVID-19 transmission likely extends beyond the county containing the livestock plant. *SI Appendix*, Fig. S3 expands our main analysis to include neighboring counties grouped by distance band, as charted in Fig. 1 and visualized in the map in *SI Appendix*, Fig. S1. We found evidence of a relationship between livestock plants and increased COVID-19 case rates up to 150 km away from a plant, further supporting the notion of community spread beyond the immediate work context.[††]

To validate and contextualize our findings, we first estimated the total excess cases and deaths related to livestock plants implied by our results. For one set of estimates, we multiplied the plant-level coefficient for excess cases and deaths related to livestock plants by the total number of plants and the average population per plant to arrive at a national total. A second approach used a binary measure for whether a county has one or more livestock plants and multiplied this coefficient by the county-level mean population and number of counties with livestock plants. The estimates resulting from this exercise were, respectively, 236,000 to 310,000 cases and 4,300 to 5,200 deaths. A summary of this calculation is shown in *SI Appendix*, Table S19.

Next, we estimated the share of cases among livestock employees relative to total excess cases in an attempt to determine the share of excess cases that may be occurring outside the livestock plants. We used the CDC's state-level aggregate count of livestock workers testing positive for COVID-19 as of May 31 across 26 states (64). Comparing this to state-level case data as of May 31, we found that livestock workers represented 2.7% of cases in these states. Using this ratio to estimate the total number of infected livestock workers among all of the cases observed in these states on July 21, we arrived at an estimate of 35,635 infected workers, $\sim$7% of the industry's entire employee base. Using our calculation of 236,000 to 310,000 cases nationwide due to livestock plants, we estimated that livestock workers represent 12 to 15% of these excess total cases. In other words, for every worker infected at a livestock plant, between seven and eight local nonworkers were ultimately infected by the end of the sample period, underscoring the high potential for community spread.

Discussion

Angrist and Krueger (65) noted that "one should always be wary of drawing causal inferences from observational data." We know of no random-assignment design that could address our research question and thereby yield the most reliable path to causal inference. The best we can do here is provide an unusually broad array of observational evidence. This includes (but is not limited to) ruling out the most obvious confounders, a cross-sectional IV, and the event-study analysis leveraging shutdown timing. A still more compelling natural experiment would leverage explicit and exogenous variation that drives livestock-plant shutdowns, i.e., an IV for the shutdowns or their timing. Unfortunately, we know of no such identifying variation.

Readers may disagree on whether our array of analyses has isolated a causal effect. Given this, and in order to be conservative, we avoided causal language throughout our text so as not to overstate the "hardness" of our method (66). This avoidance and caution stands in contrast to other recent, impactful work on COVID-19.

Still, we believe that our array of analyses constitutes the best feasible approach to shed light on the role of livestock-processing plants in the US COVID-19 pandemic. For a question of this importance, we believe there is no "harder" method available (66). As policymakers and industry leaders seek to preserve vital food-supply chains while mitigating the pandemic's spread, evidence on the potential scope of the issue is particularly valuable, as well as assessment of the relationship between temporary plant shutdowns and subsequent COVID-19 growth dynamics.

[**] A balance table for the entire sample is shown in *SI Appendix*, Table S11.

[††] We present summary statistics by distance band in *SI Appendix*, Tables S16–S18. The average number of counties in each band increases with distance. There is a clear positive relationship between COVID-19 cases and deaths in relation to livestock facilities, and the county-level mean case rate varies directly with a county's proximity to a neighboring county with a livestock facility.

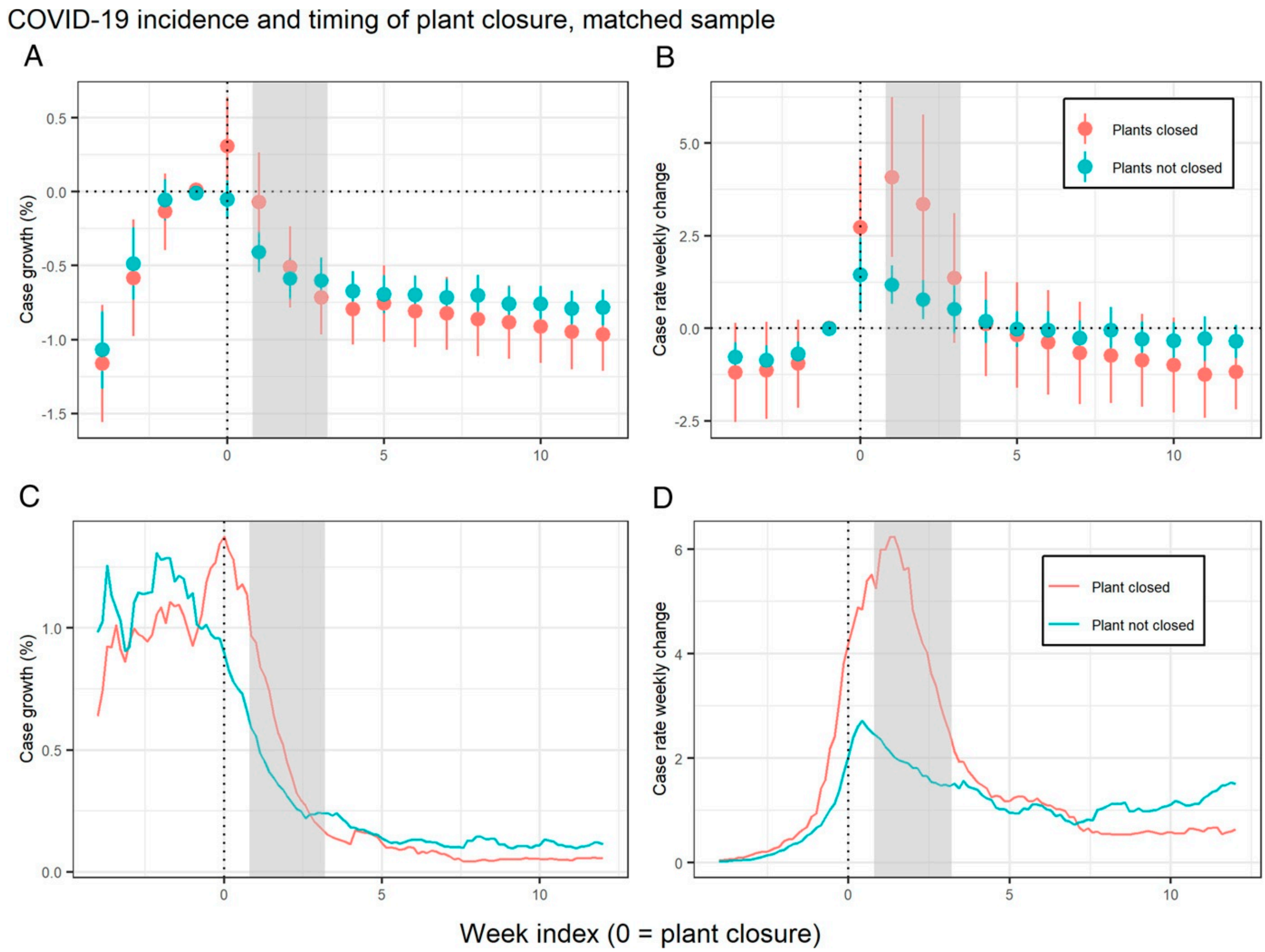

Fig. 4. Graphs match COVID-19 pretrends of control group (green lines) to counties with plant shutdowns (red lines) based on percent growth in cases (weekly log difference) in the 2 wk prior to shutdown. Selected counties are in the top quartile of growth rates among the 233 counties with livestock plants that did not have a plant shutdown. For nonshutdown counties, week 0 is assigned to the mean shutdown date, April 22, 2020. *A* and *B* plot coefficients from a panel regression, where counties are interacted with the weekly event index in terms of percent growth in cases (*A*) and change in case rates per 1,000 (*B*). Estimates are relative to the baseline trend across all counties. One week prior (week −1) is omitted as the reference level. Models control for stay-at-home orders at the state level and include a fixed effect for each county. Error bars reflect a 95% CI. *C* and *D* are daily line charts of the mean values of each group in terms of percent case growth and change in case rate, respectively. Gray shaded bars reflect the estimated period when the effect of closing a plant would have been reflected in cases (1 to 3 wk after), given that incubation periods may last up to 14 d) (62).

Although our estimate that 6 to 8% of COVID-19 cases are associated with livestock plants may appear high, it is important to recall that high levels of geographic heterogeneity in COVID-19 incidence can be explained by some combination of individual behavior, government policy, social-distancing compliance, and economic activity: The United States, for example, has 4% of the world's population, but approximately a quarter of all cases and deaths as of July 2020. When narrowing the geographic focus, we can imagine the distribution of COVID-19 incidence to be similarly clustered, if not even lumpier.

Kansas provides a telling example of the outsized role of livestock facilities: As of July 20, a total of 3,200 of 23,300 state cases (14%) were directly linked to meatpacking (67). For context, there are 17,200 employees in the animal-slaughtering industry in Kansas (68), or 0.6% of the state's population, suggesting that livestock plants had a relationship of a magnitude closer in scale to our own estimates (Kansas' estimate is 23× their labor footprint). Although the figure we are estimating in our study (6 to 8% of all US cases out of a national livestock workforce of 0.15%, or a multiplier of 40 to 53×) is larger, we believe that this finding is plausible, considering follow-on community spread; Kansas' official tally, though evidently aided by some degree of contract tracing, was reportedly hampered by lags in hiring staff and legislative actions that have inhibited tracing efforts (69). That is, the figure we have calculated could, in fact, be more complete than the Kansas figure in capturing the spread resulting from livestock plants.

Our analysis of individual meatpacking companies may present an opportunity to explore how differences in corporate structure and operating practices may account for their differential public health outcomes. In particular, the evidence that shutting down plants temporarily may be related to decreases in COVID-19 case growth presents a potentially powerful transmission mitigant. In addition, the positive relationship between COVID-19 transmission and production-line speed waivers issued to poultry plants, particularly those during the 2020 pandemic, is notable, given that these waivers are intended for plants with safe commercial production practices

Table 2. COVID-19 testing, livestock facilities, and COVID-19 incidence

	Dependent variable							
	Case rate				Death rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Livestock facility	4.07***	4.30***	4.19***	4.19***	0.07***	0.06**	0.06**	0.06**
	(0.80)	(1.23)	(1.21)	(1.20)	(0.02)	(0.03)	(0.03)	(0.03)
Testing per 1,000			0.01*	0.01*			0.0001**	0.0001**
			(0.003)	(0.003)			(0.0000)	(0.0000)
Positivity rate				0.86**				0.02**
				(0.38)				(0.01)
Controls	X	X	X	X	X	X	X	X
State FE	X	X	X	X	X	X	X	X
Observations	3,032	1,773	1,773	1,773	3,032	1,773	1,773	1,773
R^2	0.45	0.44	0.45	0.45	0.42	0.44	0.44	0.44

Regression model with cross-sectional county-level data from 31 states with livestock facilities and available data on county-level testing gathered from 31 state health departments. Dependent variables are COVID-19 cases (models 1 to 4) and deaths (models 5 to 8) per thousand. Livestock facility is the sum of beef, pork, and poultry plants in the county. Testing per thousand represents the number of tests taken per thousand people in these states as of July 14, 2020. Positivity rate is total cases divided by total tests. Controls include income per capita (log), density (population per built-up land area) and density squared, the number of freight miles traveled, and timing of first case (index of Julian day of first confirmed case), as well as proportions of the county population over the age of 70, Black, Hispanic, public-transit commuters, uninsured, frontline workers, or in nursing homes or prisons. State-level fixed effects (FE) are included in all models. SEs are clustered at state level.
$^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

and microbial control.[‡‡] This finding suggests a need for additional examination of this program.

An implication of this study is that some aspects of large meat-processing plants render them especially susceptible to spreading respiratory viruses. One potential explanation is that large plants simply entail more activity and employ more people. Because these plants provide a central location for moving products, it is plausible that a linear increase in the potential infected within the plant would entail a nonlinear response, owing to the complex and exponential nature of disease-transmission dynamics (70). Another driver may be the large physical spaces where processing occurs. Larger rooms tend to be louder and, thus, require more shouting (53), and they may require stronger climate control, which we note in our introduction may aggravate COVID-19 spread. A larger space that employees must navigate in reaching their workstations may also increase the number of workplace interactions.

More broadly, the finding that meatpacking plants may contribute to high levels of community spread underscores the potential negative public health externalities generated by the industry, which may be attributable to industrial concentration, operating practices, and labor conditions. Complicating this matter from an economic standpoint is the supply-chain choke point created by large plants disrupted by COVID-19, causing food shortages, driving up prices, and incurring substantial upstream and downstream economic losses. Cataloging and addressing the underlying factors that produced this systemic risk in the first place could not only strengthen the US food system in the face of COVID-19 and future disruptions, but also help illuminate analogous weak points in other industries and supply chains.

Materials and Methods

Our analysis used a county-level dataset of COVID-19 cases and deaths from the *New York Times*, based on reports from state and local health agencies (71). Included in counts are both confirmed and probable deaths, as categorized by states. The five county boroughs of New York City are grouped into one unit. We limited the analysis to the continental United States. Our baseline model specification takes the following form:

$$outcome_i = \beta * livestock_i + \theta * controls_i + \alpha_s + \epsilon_i, \quad [1]$$

where $outcome_i$ is the COVID-19 case or death rate in county i, β is the coefficient of interest, $controls_i$ is a vector of county-level covariates, α_s is a dummy for fixed effects in state s, and ϵ_i is the error term.

Covariate data include county-level race, ethnicity, and age structure data from the US Census and mean county-level income data from the US Bureau of Economic Analysis (72, 73). Data on nursing-home populations, incarcerated populations, uninsured populations, average household size, and work-commuting methods come from the 2014–2018 American Community Survey (74–77). Data on manufacturing establishments come from the

Table 3. Livestock facilities and county-level COVID-19 incidence, IV

	Dependent variable			
	Case rate		Death rate	
	(1)	(2)	(3)	(4)
Livestock facility	9.00***	6.12***	0.13*	0.06
	(2.80)	(1.43)	(0.07)	(0.06)
Controls	X	X	X	X
State FE		X		X
Observations	3,032	3,032	3,032	3,032
R^2	0.33	0.45	0.27	0.42

Regression model with an instrument for the presence of a livestock plant in a county using the county's livestock production value in 1959 in terms of animals sold. Livestock facility is the sum of beef, pork, and poultry plants in the county. Controls include income per capita (log), density (population per built-up land area) and density squared, the number of freight miles traveled, and timing of first case (index of Julian day of first confirmed case), as well as proportions of the county population over the age of 70, Black, Hispanic, public-transit commuters, uninsured, frontline workers, or in nursing homes or prisons. State-level fixed effects (FE) are included in models 2 and 4. SEs are clustered at the state level.
$^{*}P < 0.1$; $^{***}P < 0.01$.

[‡‡] In contrast, some plants receiving waivers had recent Occupational Safety and Health Administration violations (42).

American Economic Survey (68). Number of frontline workers were derived from Center for Economic Policy Research data (54), transforming from Public Use Microdata Area-level to the county level, assuming even allocation. The freight index is from the Federal Highway Administration's Freight Analysis Framework (78) using the variable AADTT12, the annual average daily truck traffic in 2012, which we sum across all listed highways in a given county. Data on state-level social-distancing policy come from a dataset synthesizing news articles tracking these policy measures (79–81).

Locations and characteristics of livestock processing facilities come from the USDA FSIS (82). Beef and pork livestock plants were filtered to include plants with volume of all processed products greater than 1 million pounds per month (categories 4 and 5), which account for the vast majority of US production. Poultry livestock were filtered to include plants with volumes greater than 10 million pounds per month (category 5) because that category alone accounts for the majority of US production. County-level mobility data were made accessible to COVID-19 researchers by Google (83). County-level COVID-19 testing data came from a dataset gathered from 31 state health agencies (84). Data on line-speed waivers came from the USDA FSIS (85). Data on plant closures and opening dates came from a dataset assembled from various local news reports, building on a dataset from the Midwest Center for Investigative Reporting (86, 87). Historical livestock-production data are from the 1959 USDA census of agriculture, accessed via the Inter-University Consortium for Political and Social Research (88).

Data Availability. Detailed CSV datasets concerning plant and county-level data relevant to COVID-19 employed in this study are available in Zenodo at https://doi.org/10.5281/zenodo.4069616. Further information is available in Github at https://github.com/cboulos/livestock-covid.

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