DISCUSSION PAPER SERIES

DP15022

PANDEMICS, INTERMEDIATE GOODS, AND CORPORATE VALUATION

Luc Laeven

FINANCIAL ECONOMICS

ISSN 0265-8003

PANDEMICS, INTERMEDIATE GOODS, AND CORPORATE VALUATION

Luc Laeven

Discussion Paper DP15022
Published 09 July 2020
Submitted 08 July 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

PANDEMICS, INTERMEDIATE GOODS, AND CORPORATE VALUATION

Abstract

We evaluate the role of input-output linkages and social distancing in transmitting the COVID-19 shock to the valuation of U.S. corporates. Using a new dataset on sectoral dependence on the use and sale of intermediate goods, we find that firms that depend on the sale of intermediate goods to sectors affected by social distancing are more affected by the crisis. We estimate that the indirect effect of social distancing through input-output linkages is at least as important as its direct effect. Several tests are consistent with the view that larger firms and firms with cash buffers are better able to absorb the pandemic shock.

JEL Classification: D22, D57, G01, G32

Keywords: Valuation, liquidity, cash, Intermediate goods, Pandemic

Luc Laeven - luc.laeven@ecb.europa.eu
European Central Bank and CEPR

Pandemics, Intermediate Goods, and Corporate Valuation

Luc Laeven*

June 2020

Abstract: We evaluate the role of input-output linkages and social distancing in transmitting the COVID-19 shock to the valuation of U.S. corporates. Using a new dataset on sectoral dependence on the use and sale of intermediate goods, we find that firms that depend on the sale of intermediate goods to sectors affected by social distancing are more affected by the crisis. We estimate that the indirect effect of social distancing through input-output linkages is at least as important as its direct effect. Several tests are consistent with the view that larger firms and firms with cash buffers are better able to absorb the pandemic shock.

Keywords: Valuation, Liquidity, Cash, Intermediate Goods, Pandemic
JEL Codes: D22; D57; G01; G32

* Laeven: European Central Bank and the CEPR, luc.laeven@ecb.europa.eu. Research assistance from Carl-Wolfram Horn is gratefully acknowledged. The views expressed are my own and do not reflect those of the ECB or the Eurosystem.

1. Introduction

The COVID-19 health crisis has prompted governments to take extraordinary measures to save lives, including lockdown and social distancing measures. The combined effect of the spreading of the virus and these lockdown measures has resulted in an unprecedented sharp decline in economic activity, as affected sectors were essentially shut down. Sectors were differentially affected by the crisis shock and the crisis response. For instance, the tourism industry suffered greatly due to travel restrictions while grocery stores experienced an increase in sales due to an increase in cooking at home instead of eating out.

In this paper, we study the role of firm input-output linkages and social distancing in the transmission of the COVID-19 shock to the valuation of U.S. corporates. Economic theory suggests that the initial shock to affected sectors can spill over to unaffected sectors through input-output linkages (e.g., Long and Plosser (1983); Hertzel et al. (2008); Acemoglu et al. (2012)). To the extent that firms in unaffected sectors rely on intermediate inputs and demand for products from firms in affected sectors, social distancing can disrupt the ability of firms in unaffected sectors to produce and sell goods. We would therefore expect that firms whose suppliers and customers are concentrated in industries and states that are more affected by the COVID-19 shock and related lockdown measures would experience larger stock price declines compared to otherwise similar firms.

To assess the significance of this spillover channel from input-output linkages, we construct a new dataset of the sectoral dependence on the use and sale of intermediate goods, using input-output tables from the U.S. Bureau of Economic Analysis, which we combine with information on lockdown and social distancing measures at the state and sectoral level, including information on each sector's physical contact-intensity from Kóren and Petö (2020) based on data from O*NET and the designation of (non)essential industries by the U.S.

Department of Homeland Security. We measure the initial COVID-19 shock using information on the number of reported COVID-19 cases and deaths in the state. We combine all this information with financial and stock price data from Compustat.

As is standard in asset pricing, we control for the ratio of book equity to market equity and firm size (market value) as determinants of equity returns (Fama and French (1992)). We also control for cash holdings of the firms. The pandemic's negative impact on firm cash flows led to "dash for cash" and a tightening of liquidity constraints. Firms with larger cash holdings are expected to better withstand such liquidity shocks and this should be reflected in less severe stock price declines than for otherwise identical firms (e.g., Harford (1999); Bates, Kahle, and Stulz (2009)). Finally, we control for leverage because more highly levered firms may become financially constrained during a financial crisis (Giroud and Mueller (2017)).

Our analysis focuses on the first quarter of 2020. This period covers the outbreak of the virus in Wuhan, China, which was reported to the World Health Organization (WHO) on December 31, 2019, the first confirmed case of local transmission in the U.S. in late January, the declaration of a public health emergency by the Trump administration on January 31, 2020, the designation by the WHO of COVID-19 as a global pandemic on March 13, 2020, the guidance on (non)essential critical industries issued by the U.S. Department of Homeland Security on March 19, 2020, and a series of lockdowns and stay at home orders at state level during the second half of March 2020. We focus on stock returns over this period, conditioned on pre-determined firm characteristics measured as of end of 2019.

We find that the returns of firms that operate in sectors that are more sensitive to social distancing measures are more adversely affected by the crisis. Moreover, we find a role for input-output linkages in the sense that firms that depend on the sale of intermediate goods to sectors affected by social distancing measures are more affected by the crisis. Several tests are consistent with the view that bigger firms and firms with larger cash buffers are better able to withstand these shocks, consistent with the notion that scale and deep pockets can help to buffer the shock. Both the direct effects of social distancing and its indirect effects through input-output linkages appear to be important drivers of stock prices during the outbreak of the pandemic. Our estimates imply that a one standard deviation increase in the industry's share of workers affected by social distancing (the direct effect) is associated with a decline in stock returns of 2.7%, while a one standard deviation increase in the fraction of output sold to social-distancing affected sectors (the indirect effect) is associated with a decline in stock returns of 3.1%. The indirect effect of social distancing from the sale of products to other firms is therefore estimated to be quantitatively at least as important as the direct effect from social distancing. This implies that lockdowns impose large negative externalities on firms through input-output linkages, even for firms that are not directly affected by social distancing measures.

Our paper is related to ongoing research on the nature of the COVID-19 shock and its transmission to the real economy. For instance, Guerrieri et al. (2020) study under which circumstances the supply shock caused by COVID-19 in the form of shutdowns, layoffs and firm exits also constitutes a drop in aggregate demand. They show that this supply shock can trigger changes in aggregate demand that are possibly larger than the supply shocks themselves especially when consumers are liquidity constrained. Intuitively, if workers in the affected sectors lose their jobs and income, their consumption drops significantly if they are credit constrained and have a high propensity to consume. To make up for this, workers in the unaffected sectors would have to increase their consumption of the remaining goods sufficiently. This requires a high degree of substitution across goods of different sectors. If goods are not sufficiently close substitutes, aggregate demand contracts more than supply and employment in the unaffected sectors falls.

Existing analysis has also shown that unaffected sectors rely to a large extent on intermediate inputs and demand for products from affected sectors. For instance, Leibovici et al. (2020) consider that the activity of industries where people tend to work in close proximity to one another can be expected to be more sensitive to social-distancing measures. They show that such contact-intensive industries are an important source of demand for firms in other industries. Kóren and Petö (2020) show that many U.S. industries rely heavily on teamwork, customer contact and physical presence in their operations, and that these firms are particularly vulnerable to social distancing policies. Together such vulnerable industries account for about 50 million of employment in the United States. We build on this work by showing how the pandemic shock is transmitted to stock prices via input-output linkages.

Baqaee and Farhi (2020a) study the role of input-output linkages in the propagation of negative supply shocks caused by COVID-19 and find that these shocks get amplified because of complementarities in consumption and production that create supply bottlenecks and disrupt supply chain networks. The amplification is stronger when shocks are more heterogeneous across sectors and when reallocation across sectors is difficult. While our paper also considers the role of input-output linkages in the transmission of the COVID-19 shock, the approach taken is different. Baqaee and Farhi (2020a) build a macroeconomic model to quantify the propagation of the COVID shock while we conduct an empirical analysis at the firm level of how the COVID shock is propagated to firm stock prices through input-output networks.

Research is also exploring how firms' earnings forecasts and stock prices have been affected by the shock. For instance, Gormsen and Koijen (2020) estimate the impact of the COVID-19 shock and subsequent policy responses on stock prices and investors' expectations about the economic growth path. Landier and Thesmar (2020) find that short-term earnings expectations have been revised down sharply with an increase in dispersion while long-term earnings expectations have not reacted as much. Alfaro et al. (2020) show that stock prices react strongly to unanticipated changes in projected COVID-19 cases. Ramelli and Wagner (2020) find that the stock prices of internationally-oriented firms and firms with lower cash holdings were particularly negatively affected, and Pagano et al. (2020) find that stock prices of firms that operate in sectors that are more affected by social distancing measures are particularly negatively affected during the COVID-19 outbreak. We contribute to this literature by considering the role of input-output linkages.

There is also ongoing economic research that is incorporating economic decision-making into epidemiological models, by allowing for the interaction between economic decisions and rates of infection. For instance, Eichenbaum et al. (2020) develop a model where working and consumption influences the rate at which infections spread. The epidemic induces people to consume and work less to reduce the chance of getting infected, causing a recession. Supply is affected because the epidemic exposes people who are working to the virus, and people react to that risk by working less. Demand is affected because the epidemic exposes people who are purchasing consumption goods to the virus, and people react to that risk by reducing their consumption. This leads to an externality—people infected with the virus do not internalize the effect of their consumption and work decisions on the spread of the virus. Glover et al. (2020) show that there can also be large distributional implications of shut-down policies. Health benefits are concentrated among the old and economic costs are concentrated among the young and especially those working in sectors that are being shut down. In our work we abstract from these distributional consequences except to the extent that they are reflected in stock prices.

Finally, our paper speaks to the literature on how economic and financial shocks propagate across firms to affect firm performance and valuation. The literature has focused on a wide range of transmission channels, varying from financial accelerators arising from shocks to wealth, collateral or bank liquidity shocks (e.g., Khwaja and Mian (2008); Ivashina and Scharfstein (2010); Chaney et al. (2012); Chodorow-Reich (2014); and Gilje et al. (2016)) to demand channels (Giroud and Mueller (2017)).

More recently, this literature has also considered the role of economic and financial networks in the propagation of shocks to firms, including through internal firm networks (Giroud and Mueller (2019)), trade credit networks (Jacobson and von Schedvin (2015)) and networks of suppliers and customers (Acemoglu et al. (2012); Di Giovanni et al. (2014); Barrot and Sauvagnat (2016); Bigio and La'O (2016); and Baqaee and Farhi (2020b)). We contribute to this literature by considering how an exogenous shock to the composition of the network of suppliers and customers is transmitted to firms through input-output linkages. Much of this literature takes the structure of the input-output network as given. The COVID-19 shock and associated lockdown measures essentially stopped activity in parts of the input-output network. This shock was exogenous to the firm because it was guided by health considerations and was not systematically related to firm conditions. This provides a unique setting to study the role of networks in the transmission of shocks to the economy.

Perhaps most closely related to our paper is a recent paper by Ding et al. (2020). They also study the effect of the pandemic on stock prices. They find that firms' stocks returns are negatively affected by the number of COVID-19 cases in the country and that this impact is more pronounced for firms that depend more on global supply chains, that have lower corporate social responsibility scores, and that have more anti-takeover devices. Our work complements their study. Their focus is on the role of firm characteristics (notably corporate governance traits), while our focus is on how firm characteristics (input-output linkages) interact with government interventions (lockdowns, essential industries and social distancing measures) to shape shock prices. Another difference is that their study is global while we focus on U.S. firms.

The paper proceeds as follows. Section 2 gives a brief primer on input-output tables. Section 3 presents the data and descriptive statistics. Section 4 presents the basic model. Section 5 presents the empirical evidence. Section 6 presents robustness tests. Section 7 concludes.

2. Input-output linkages

Firms often depend on each other for inputs or the sale of products. Such firm relationships can be described as input-output linkages that can be summarized in the form of input-output tables. These are inter-industry matrixes that show how outputs from one sector are sold to or used as inputs by another sector. Leontief (1936) was the first to depict inter-industry relationships within an economy using input-output tables and matrix algebra. Let us for illustrative purposes take a simple example of a closed economy with n sectors. Each sector produces x_i units of a single homogeneous good. Assume the j-th sector, in order to produce 1 unit, uses a_{ij} units from sector i. Furthermore, assume that each sector sells some of its output to other sectors as intermediate output and some of its output to consumers as final demand. Let d_i be final demand in the i-th sector. Then we can write the production of each sector as a function of the production of all other sectors and final demand as follows:

$$x_i = a_{i1}x_1 + a_{i2}x_2 + \ldots + a_{in}x_n + d_i \tag{1}$$

Let A be the full matrix of coefficients a_{ij}, x the vector of total output, and d the vector of final demand, then we can aggregate at the level of the overall economy the previous expression at the sectoral level to obtain:

$$x = Ax + d \tag{2}$$

which indicates that total output equals intermediate output plus final demand. We can rewrite this expression as follows:

$$x = (I - A)^{-1}d \quad (3)$$

The Leontief model assumes that each sector produces a homogenous good and that each industry's output is produced using a unique set of inputs. In reality, industries produce a variety of products. To deal with this, statistical agencies create separate matrixes for the uses and the supply of products between industries. These are no longer transposed versions of one another. This so-called supply-use framework comprises two tables: the supply table and the use table (for further details, see Young, Howells, Strassner and Wasshausen (2015)).

The supply table presents the total domestic supply of goods and services from both domestic and foreign producers that are available for use in the domestic economy. Industries appear across columns and commodities across rows, and each cell indicates the amount of each commodity that is produced domestically by each industry. If one aggregates row entries across columns for a given sector, one obtains the total products sold by a given industrial sector.

The use table shows the use of this supply by domestic industries as intermediate inputs and by final users as well as the value added by industry. Industries appear across columns and commodities across rows, just like in the supply table. However, each cell indicates the amount of a commodity purchased by each industry as an intermediate input into the industry's production process. If one aggregates column entries across rows for a given sector, one obtains the total intermediate inputs used by a given industrial sector. Column totals indicate total industry output which is the sum of intermediate inputs and value added (i.e., compensation of employees and gross operating surplus), while row totals denote total production, which is the sum of intermediate products and final demand.

Central to our analysis will be that input-output linkages can be severely disrupted by the pandemic. Specifically, sectors differ in their sensitivity to social distancing. To the extent that firms depend differentially on the use or supply of intermediate products from such sectors, the pandemic will differentially affect firms through their network of input-output linkages. Let s_j be the fraction of production of sector j that would disappear in case of social distancing. Then a firm in sector i is not only directly affected by the impact of social distancing in terms of a loss in final demand, but also indirectly through its dependence on (the sale or use of) intermediate products from all affected sectors j. The output of sector i would then be reduced to:

$$(1 - s_i)x_i = a_{i1}(1 - s_1)x_1 + a_{i2}(1 - s_2)x_2 + \ldots + a_{in}(1 - s_n)x_n + (1 - s_i)d_i \tag{4}$$

Let s be the vector of the fraction of output that is lost because of social distancing. We can then rewrite equation (4) at the level of the economy as a whole as:

$$(1 - s)'x = A(1 - s)'x + (1 - s)'d \tag{5}$$

or

$$(1 - s)'x = (I - A)^{-1}(1 - s)'d \tag{6}$$

In the above, $As'x$ is the fraction of affected intermediate output. This can be computed based on either the supply or the use table. When using the supply table, we obtain the fraction of output from the sale of intermediate products to affected industries, and when using the use table we obtain the fraction of output from the use of intermediate products from affected industries.

3. Data and Descriptive Statistics

We obtain data on stock prices and firm financial statements for US listed firms from Compustat. We use this data to compute total stock returns over the first quarter of 2020, which is the period during which the pandemic broke out and lockdown measures were put in place, for a total of 3,274 firms. In a robustness check, we compute stock returns over the first four months of 2020 because some of the implications of lockdowns and the severity of the health shock may not have been fully reflected in share prices by the end of March as there was much uncertainty about the path of the pandemic. We use the financial statements data to construct the Book-market variable, defined as the book-to-market value of the firm's stock at calendar year-end. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. Size is the logarithm of total assets (in millions of US dollars) at calendar year-end. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile because two firms have negative book values for equity. Cash is the ratio of cash and cash equivalents to total assets. We also use Compustat to collect information on the primary industry the firm operates in, at the four-digit level.

We complement these firm-level variables with information on health statistics and lockdown measures at the state level. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s and Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. We obtain data on reported COVID-19 cases at the state level from the Centers for Disease Control and Prevention (CDC) and the COVID Tracking Project (https://covidtracking.com/) as of end-March 2020. Data on state-level population is obtained from the U.S. Census of July 2019. Lockdown equals one if the state governor has issued a statewide lockdown as of the beginning of April 2020, and zero otherwise. Information on announced statewide lockdowns is obtained from each state governor's website.

We also include information on the sensitivity of industries to lockdown and social distancing measures. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020), at the three-digit NAICS level. They use data from the Occupational Information Network (O*NET) to collect information on the job characteristics of a given occupation, as previously done by Autor and Dorn (2013). They focus on three job characteristics that are related to social distancing measures: teamwork, customer contact and physical presence. They then compute for each sector the share of workers whose job requires a high level of teamwork, customer contact and physical presence. The result is a variable that captures the fraction of workers in social-distancing affected occupations. This measure is also used in Pagano et al. (2020).

Non-essential is a variable that indicates whether the Cybersecurity and Infrastructure Security Agency (CISA) of the Department of Homeland Security considers the industry to be nonessential. On March 19, 2020, by which time the pandemic had taken systemic proportions in the United States, CISA published a list that identified essential critical infrastructure workings during the COVID-19 response (see CISA (2020)). This list served as guidance to the states to indicate which industries were to remain open in spite of state-level lockdown measures. Most states followed this list. Industries that were not on this list were considered nonessential and in most cases were temporarily shut down during periods of lockdown.

A key part of our data is information on (affected) input-output linkages. We obtain the use and supply input-output tables from the U.S. Bureau of Economic Analysis (BEA) for the year 2012 available from the BEA website (https://www.bea.gov/industry/input-output-accounts-data). We use the detailed tables, which offer the most disaggregated information available and contain input-output matrixes for 405 industries.

Total-sold is the fraction of total production sold to other industries. It is computed using the supply table by aggregating row entries across columns for a given sector. Total-intermediate is the fraction of total output consisting of intermediate products from other industries. It is computed using the use table by aggregating column entries across rows for a given sector.

We combine the input-output data with the distancing variable to identify the part of the network of suppliers and customers that is disrupted by social distancing. Affected-sold is the fraction of total production sold to industries affected by social distancing. It is computed for a given sector by aggregating row entries from the supply table across columns, multiplied by each entry's distancing value according to Kóren and Petö (2020). Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. It is computed for a given sector by aggregating row entries from the using table across columns, multiplied by each entry's distancing value according to Kóren and Petö (2020).

Similarly, for robustness, we compute Affected-sold (nonessential), which is the fraction of total production sold to nonessential industries, and Affected-intermediate (nonessential), which is the fraction of total output consisting of intermediate products from nonessential industries. Affected-sold (nonessential) is computed for a given sector by aggregating row entries from the supply table across only those columns of industries that not designated as essential by CISA, while Affected-intermediate (nonessential) is computed for a given sector by aggregating row entries from the use table across only those columns of industries that not designated as essential by CISA.

We merge all data at the four-digit NAICS level and use standard concordance tables to match the firm, distancing, nonessential designation, and input-output data. The Distancing variable has missing observations for four sectors but data availability is such that we can still compute the input-output variables for those sectors. We drop those sectors from the analysis for which there are no firms with stock prices.

There is much variation in the impact of the crisis on stock prices across sectors (Table 1). The hardest hit sector is the mining, oil and gas sector, which was adversely affected by the sharp drop in commodity prices as the global economy came to a halt. On average, stock prices declined by 53.4 percent in this sector. Next are the entertainment and the hotel and restaurant sectors, which declined by 45.2 percent on average. Both sectors were largely closed down because of lockdown measures. While no sector escaped a decline in stock prices on average, some sectors fared relatively well, such as the agriculture and the health sectors, which both saw a decline in stock prices of about 14 percent. Both sectors are regarded as essential sectors in the provision of food and health services, respectively, and some firms in these sectors saw an increase in demand for their products (e.g., drugs and medications, masks). Across all sectors, the average firm's stock price declined by 25.6 percent during the crisis, which makes it one of the sharpest stock market crashes over a three-month period in history.

The descriptive statistics of our main regression variables are reported in Table 2. There is much variation in stock returns over this period, and by the end of April, the average firm had recovered about half of the loss accumulated over the first three months of the year. Firms went into the crisis with very different levels of cash holdings. The average firms had sizeable cash holdings (and equivalents) of about 21.7 percent of total assets but 25 percent of the firms had low cash holdings of below 2.7 percent of their total assets.

The spread of the pandemic showed much variation from state to state. By the end of March, the worst hit state had 389.6 cases that were tested positive for the virus for every 100,000 people, while the least hit state had 8.9 reported cases per 100,000 people. Similarly, the number of COVID-19 deaths per 100,000 people varied from a low of 0 to a high of 8. Most states ended up imposing a statewide emergency lockdown on nonessential businesses and inhabitants more generally in early April, the six exceptions being Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, and Utah.

On average, about 37.1 percent of the workers were negatively affected by social distancing, but the variation across industries is large, varying from a low of 13 percent in the apparel manufacturing industry, which is heavily automatized, to a high of 91 percent in health and personal care stores. Moreover, 38 of the 216 industries (or 17.6% of the total) were considered as nonessential and for the most part being temporarily closed down.

In terms of input-output linkages, the average industry relies for 10.3 percent of its production on the sale of goods and services to other industries, varying from a low of 0 percent in the grain and vegetable farming industries to a high of 84.4 percent in the water utilities industry. Moreover, the average industry depends for 48.0 percent of its output on the use of intermediate inputs from other industries, varying from a low of 0 percent in the automobile dealers industry to a high of 87.9 percent in the grain and oilseed milling industry, which depends heavily on the agricultural sector for its inputs.

The average industry depends for about 2.7 percent of its total production on the sale of products to industries adversely affected by social distancing, but this can be as high as 26.4 percent in the case of the Automotive repair and maintenance (NAICS 8111) industry, which depends heavily on the sale of products to the Motor vehicle and parts dealers (NAICS 4441) industry.[1] Dependence on intermediate inputs from social distancing-affected sectors also varies across sectors, and is generally higher than dependence on the sale of products to other sectors. The average industry depends for about 14.0 percent of its output on the supply of intermediate inputs from industries affected by social distancing, but this can be as high as 27.2 percent in the case of the Nonferrous metal production and processing (NAICS 3314) industry. This industry depends heavily on the Metal ore mining (NAICS 2122) industry for its inputs, which is an industry with a social distancing value of 71.0 percent, and to a lesser extent on the Electric power generation, transmission, and distribution (NAICS 2211) industry, which has a social distancing value of 46.0 percent. Table 2 also presents summary

[1] In fact, this variable takes on its highest value of 54.8 percent for the Radio and Television Broadcasting industry but this industry is dropped from our regressions because it does not have any listed firms.

statistics for the affected sold and intermediate product variables based on the designation of nonessential industries instead of social distancing.

Table 3 shows the correlation matrix of our main regression variables. Most of the covariates of interest display a low correlation. A notable exception is the correlation coefficient between the Cash and the Social distancing variables which is minus 43 percent, indicating that firms in sectors that are particularly sensitive to social distancing already started out with smaller buffers to absorb shocks, everything else equal.

Appendix Table 1 shows the underlying data for the industry-level variables at the two-digit NAICS sector level and Appendix Table 2 presents our state-level data. Note that in the empirical analysis we use the industry-level data at the four-digit NAICS level.

4. The Basic Model

Our basic model aims to gauge both the direct effect of social distancing and its indirect effect through input-output linkages on the valuation of firms. To this end, we extend the standard two-factor Fama and French (1992) model of stock returns with variables capturing COVID-19 cases and lockdown measures at the state level, social distancing and input-output linkages at the sectoral level, and firm characteristics.

Specifically, we estimate versions of the following model:

$$Return_i = \alpha + \beta_1 \cdot Firm\ traits_i + \beta_2 \cdot Infections\ and\ lockdowns_k + \beta_3 \cdot Affected\ industry_j + \varepsilon_i \tag{7}$$

where $Return_i$ is the compounded stock return of firm i over the first quarter of 2020, $Firm\ traits$ is a set of firm-level variables, $Infections\ and\ lockdowns$ is a set of state-level variables, $Affected\ industry$ is a set of industry-level variables, i denotes firm i, j denotes industry j, k denotes state k, α denotes a constant, and ε_i is the error term with the usual properties.

More specifically, $Firm\ traits \in \{BM, Size, Cash, Leverage\}$ is a set of firm-level control variables measured at fiscal year-end 2019, including the book-to-market ratio (BM) and the log of total assets ($Size$), which are the two factors in the Fama and French (1992) model; the cash-holdings-to-total-assets ratio ($Cash$), to proxy for the firm's cash buffers; and the total-debt-to-total-assets ratio ($Leverage$), to proxy for the debt burden of the firm. We expect a positive coefficient β on the $Cash$ variable because firms with larger cash holdings should be able to better withstand the liquidity shocks from the pandemic crisis compared to otherwise identical firms (e.g., Harford (1999); Bates, Kahle, and Stulz (2009)), and we expect a negative coefficient β on the $Leverage$ variable because highly levered firms may become financial constrained during the crisis (Giroud and Mueller (2017)).

$Infections\ and\ lockdowns \in \{Cases/Pop, Lockdown\}$ is a set of state level variables, including $Cases/Pop$, which is the number of COVID-19 cases divided by the total population in the state in 100,000s, measured at the end of March 2020, to proxy for the severity of the health shock from the pandemic, and $Lockdown$, which indicates whether state-wide lockdown measures have been put in place by the end of the first quarter of 2020. We expect a negative coefficient β on $Cases/Pop$ because it reflects the depth of the health crisis and we expect a negative coefficient β on $Lockdown$ because lockdown measures deepen the economic downturn by halting activity. Of course, to the extent that firms operate and sell goods nationwide, their stock returns may be more affected by the health dynamics of the pandemic and lockdown measures at the country level as opposed to the state level, which would mute the size of the estimated coefficients on the state-level variables.

$Affected\ industry \in \{Distancing, Total - sold,\ Total - intermediate,$ $Affected - sold, Affected - intermediate\}$ is a set of industry level variables, including $Distancing$ which is the share of the industry's workers whose job is adversely affected by social distancing measures; $Total - sold$ which is the fraction of the industry's total production that is sold as intermediate output to other industries, $Total - intermediate$, which is the fraction of the industry's total output consisting of intermediate products from other industries, $Affected - sold$ which is the fraction of total production sold to industries affected by social distancing, and $Affected - intermediate$ which is the fraction of total output consisting of intermediate products from industries affected by social distancing. Taken together, the variables $Total - sold$ and $Total - intermediate$ capture the importance of input-output linkages, while the variables $Affected - sold$ and $Affected - intermediate$ capture the transmission of social distancing measures through input-output linkages.

We expect a negative coefficient on $Distancing$ because firms that operate in industries where work requires team work, customer contact and physical presence can be expected to be more adversely affected by social distancing measures. To the extent that input-output networks are disrupted by lockdowns and social distancing measures, we also expect negative coefficients on the input-output variables (e.g. Long and Plosser 1983; Hertzel et al. 2008; Acemoglu et al. 2012). We expect effects to be more pronounced for firms that rely on intermediate inputs and demand for products from firms in sectors that are more adversely affected by lockdown and social distancing measures, because the ability of such firms to produce and sell goods will be more adversely affected. We therefore expect negative coefficients on the variables $Affected - sold$ and $Affected - intermediate$. We expect the effects to be more pronounced for products sold as compared to intermediate inputs, because the pandemic triggers a sharp drop in demand, which immediately hits the demand for products from other sectors, while firms may be able to rely on existing inventories of intermediate products to buffer the shock to the supply of intermediate inputs. Input-output linkages are measured as of end-2012, which is the latest year prior to the outbreak of the pandemic for which input-output tables are available.

We estimate the model using OLS with standard errors clustered at the state-sector level. All explanatory variables except the health shock and the lockdown response measures are lagged to mitigate concerns about reverse causality.

In extensions of our basic model, we consider interactions between the explanatory variables to capture differential effects of the shock across firms based on firm traits and industry characteristics. Specifically, we estimate versions of the following extended model:

$$Return_i = \alpha_j + \alpha_k + \beta_1 \cdot Firm\ traits_i +$$
$$\beta_2 \cdot Infections\ and\ lockdowns_k \cdot Affected\ industry_j +$$
$$\beta_3 \cdot Firm\ traits_i \cdot Affected\ industry_j + \varepsilon_i \qquad (8)$$

Where α_j and α_k capture industry and state-level fixed effects, respectively. Our main coefficients of interest are the coefficient vectors β_2 and β_3, which capture the disproportional effects of local infections, local lockdowns and initial firm conditions stemming from being in an industry that is generally more affected by lockdowns and social distancing measures. We expect that the returns of firms operating in industries more affected by lockdowns and social distancing measures are disproportionally hit when these firms are also located in more affected locations (i.e., more COVID cases and local lockdowns) and when these firms hold lower cash buffers. Moreover, we expect that this differential effect is more pronounced when firms depend on other industries that are more affected by social distancing for their sales and inputs.

5. Empirical Results

Table 4 reports the results from the estimation of our baseline model in equation (7) without the inclusion of state-specific or industry-specific variables. Standard errors in all regressions are adjusted for clustering at the state-sector level. Column (1) reports the results when including only the Fama and French (1992) factors driving stock prices. These factors show up as important drivers of stock prices over this period. On average, larger firms and firms with higher book-to-market value (i.e., value firms) tend to underperform, other things equal.

We then extend the model to include a proxy for cash holdings. The results, presented in Column (2), show that firms with larger cash holdings fared significantly better than other firms during this period, consistent with the view that larger cash buffers allowed firms to better absorb the shock. The economic effect of cash holdings is significant. A one standard deviation increase in the cash ratio (0.277) implies a stock return that is 7.9% higher, which is sizeable compared to the average stock return of -25.6% over this period.

Controlling for financial leverage, included in column (3), does not add any explanatory power. This could be because financial leverage has two opposite effects on the ability to absorb the shock. On the one hand, higher leverage may increase the probability of financial distress during the crisis; on the other hand, higher leverage may indicate an easier access to cash from preexisting credit lines. Together, these firm-level variables explain about 8.7 percent of the variation in stock returns over this period, suggesting that other factors play an important role in driving stock returns over this period.

In Table 5, we expand the model with the inclusion of state-level variables capturing the health shocks from the pandemic (Cases/pop and Deaths/pop) and the lockdown responses imposed by state level governments (Lockdown). In our sample, none of these factors enters significantly. One explanation could be that many of the firms in our sample operate outside of the states in which they are headquartered and sell their products nationwide. Publicly listed firms tend to be large and operate nationally, either directly through subsidiaries or through a national network of agents selling their products. Local shocks can therefore be expected to play a less important role for these firms than for smaller, privately owned firms whose clientele is often more localized. We should therefore not conclude that local state-level shocks did not matter for the corporate sector as a whole.

Consistent with this result, we find that when we replace the state-level variables with state fixed effects in column (4), the model does not gain in explanatory power. We conclude that local health shocks and local government responses to the shock do not play a first-order effect for the firms in our sample. What matters for these firms that tend to operate nationally is the large systematic shock at national level.

We next turn to the core part of the analysis by enriching the specification with the inclusion of variables capturing social distancing and dependence on input-output linkages. The results are presented in Table 6. We find that firms that operate in sectors that are more sensitive to social distancing are more adversely affected by the crisis (Column 1). The economic effect of social distancing on stock prices is substantial: a one standard deviation increase in Distancing (0.184) implies a decrease in the stock return of 2.7%, which is sizeable compared to the average stock return of -25.6% over this period.

When we include the Total-sold and Total-intermediate variables to capture the importance of input-output linkages, we find that dependence on the supply or sale of intermediate products in and of itself does not drive stock prices over this period (Column 2 and 3). However, when we focus on the part of the network of suppliers and customers that is adversely affected by social distancing through the inclusion of the Affected-sold and Affected-intermediate variables (Column 4 and 5), we find a significant role for input-output linkages. In particular, the returns of firms operating in sectors dependent on the sale of products to (social distancing) affected firms are significantly lower than for otherwise identical firms. This implies that firms are not only directly affected by social distancing (as captured by the Distancing variable) but also indirectly through their dependence on other firms that are affected by social distancing (through the Affected-sold variable).

The economic effect of being dependent on the sale of products to affected industries is substantial: based on the estimates in Column 4, we find that a one standard deviation increase in Affected-sold (0.041) implies a decrease in the stock return of 3.1%, which is sizeable compared to the average stock return of -25.6% over this period. The indirect effect of social distancing from the sale of products to other firms is therefore quantitatively at least as important as the direct effect from social distancing.

We find that these indirect effects from disrupted input-output linkages apply only to the sale of products, not to the reliance on the supply of intermediate products. One explanation could be that firms with a large dependence on the sale of products to affected firms experience an immediate drop in demand for their products as these affected firms are temporarily shut down and finding new customers is difficult. Firms that depend mainly on the supply of intermediate products, on the other hand, may be able to absorb shocks coming from suppliers of intermediate products, for instance by relying on existing inventories or turning to other suppliers in their networks that are less adversely affected. In Table 8, we test for this possibility by conditioning the effects of input-output linkages on firm size and other firm characteristics, based on the notion that larger firms may find it easier to absorb these shocks.

In Table 7, we condition the effects of input-output linkages on state-level variables to test for the possibility that the effects of social distancing and input-output linkages vary across states depending on the size of the health shock and the lockdown responses. We find that a decrease in the number of COVID-19 cases boosts stock returns more when the dependence on intermediate inputs is lower (column 3). However, the economic effect of this result is relatively small. The marginal effect of an interquartile reduction in dependence on intermediate inputs when COVID-19 cases decrease by its interquartile range is only 0.3%. This small effect is hardly surprising given the results in Table 5 that local shocks are less important than nationwide shocks for the firms in our sample. We find no evidence of differential effects for social distancing or dependence on intermediate sales to affected industries (columns 1 and 2).

In Table 8, we estimate a version of equation (8) where we allow for the effects of social distancing and input-output linkages to vary with firm characteristics. Specifically, we include interactions between the industry-level variables and the firm traits considered thus far. These regressions also include state and industry fixed effects to absorb any unobserved state or industry factors. The purpose of these regressions is to test whether firm size or cash holdings can act as a stabilizing force to counter the adverse effects of social distancing measures on firm values. Theory suggests that firm size and cash holdings can help firms absorb financial shocks and disruptions to supplier and customer networks. Larger firms may be in a better bargaining position than smaller firms to sell or acquire goods in oligopolistic markets (e.g., Stigler (1964); Lustgarten (1975)). Moreover, when external finance is costly, firms with deeper cash pockets will find it easier to continue to pay workers, creditors, and suppliers and deal with the negative aggregate demand shock (Almeida, Campello, and Weisbach (2004)).

We find that the stocks of firms that are more sensitive to social distancing outperform when they have relatively high book-to-market values (i.e., value stocks), they are larger, and they have relatively large cash holdings (column 1). The estimated economic effects are substantial. For instance, a firm that is at the 75th percentile of the cash ratio (0.300) would experience an increase in the stock return that is 4.0% higher compared to a firm that is at the 25th percentile of the cash ratio (0.027) when moving from an industry that is at the 25th percentile of Distancing (0.210) to an industry that is at the 75th percentile of Distancing (0.500), when all other variables are evaluated at the mean. This is a sizeable effect compared to the average stock return of -25.6% over this period. In other words, the returns of less cash rich firms are disproportionately affected by social distancing.

Similarly, a firm that is at the 75th percentile of the size distribution (8.076) would experience an increase in the stock return that is 5.2% higher compared to a firm that is at the 25th percentile of the size distribution (4.812) when moving from an industry that is at the 25th percentile of Distancing (0.210) to an industry that is at the 75th percentile of Distancing (0.500), when evaluated at the mean. This is a sizeable effect compared to the average stock return of -25.6% over this period. In other words, the returns of smaller firms are disproportionately affected by social distancing.

Moreover, we find that the previously identified effect of Affected-sold is less pronounced for larger firms, indicating that larger firms are better able to absorb the collapse in demand from other firms that are affected by social distancing (column 2). The interaction with Cash holdings has the expected sign but the coefficient is not statistically significant. The effect of Affected-intermediate does not vary by the firm characteristics considered (column 3).

The estimated economic effect of the interaction between firm size and Affected-sold is substantial. Based on the estimates in column 2, we find that a firm that is at the 75th percentile of the size distribution (8.076) would experience an increase in the stock return that is 1.7% higher compared to a firm that is at the 25th percentile of the size distribution (4.812) when moving from an industry that is at the 25th percentile of Affected-sold (0.005) to an industry that is at the 75th percentile of Affected-sold (0.031), when all other variables are evaluated at the mean. This is a sizeable effect compared to the average stock return of -25.6% over this period. In other words, the returns of smaller firms are disproportionately affected when they depend on sales of products to affected industries.

6. Extensions and Robustness Tests

We now consider a number of extensions and robustness checks of our main results. Thus far, we have estimated models with stock returns computed over the first three months of 2020. On the one hand, it is natural to end the sample period in March because in April the stock market experienced a remarkable turnaround supported by large-scale fiscal and monetary policy support. It is likely that these support measures differentially affected firms, and that extending the sample period to April would therefore confound the analysis. On the other hand, the severity of the health shock may have only become fully priced in by stock markets in April, when a V-shaped recovery became increasingly unlikely. Either way, it seems meaningful to check whether results are robust to the inclusion of the month of April in the computation of stock returns. The results are presented in Table 9. We find that our main results are qualitatively similar when using returns computed over the longer period. We again find that cash-rich firms and firms that are less exposed to social distancing outperform otherwise identical firms. Moreover, firms that tend to rely on sales of products to affected sectors underperform otherwise identical firms, and this effect is more pronounced for smaller firms.

A core part of our analysis is how social distancing effects are transmitted through input-output linkages. This part of the analysis critically depends on identifying sectors that are hit hard by social distancing and lockdown measures. For the main analysis of the paper we use Kóren and Petö (2020)'s measure of the share of an industry's employment affected by social distancing as measure for an industry's dependence on social distancing. Another way to identify sectors hit hard by restrictions due to the virus is to classify industries into those that are essential and those that are non-essential, based on the CISA guidance. We then consider all non-essential industries to be the affected industries, and compute the input-output variables based on this definition of whether or not an industry is affected. Just as for industries affected by social distancing, we would expect a stronger effect for firms in the essential sector with stronger links to firms in non-essential sectors. The results are presented in Table 10.

Results are broadly insensitive to how we define affected industries, although the negative effect of being in a non-essential industry is not statistically significant (column 1). Indeed, the correlation between non-essential and social distancing is low, indicating that the two variables capture different aspects of how firms are affected by restrictions due to the virus. There are strong reasons to believe that the social distancing measure more accurately captures the impact of the virus, because industries that are deemed essential but sensitive to social distancing will nevertheless be strongly impacted by the crisis because consumers and producers will reduce activity in this sector through social distancing, despite the sector being deemed essential by authorities. We continue to find that firms that depend on the sale of products and services to affected sectors underperform otherwise identical firms (column 2).

In unreported results we have also considered whether the results in Table 8 vary by state through the inclusion of triple interactions between the firm-level, industry-level, and state-level variables. Given that returns do not respond to the state-level variables (Table 4), it should not come as a surprise that these triple interactions do not enter significantly.

Finally, we consider whether results are sensitive to using information on the number of reported COVID-19 cases for end of April instead of end of March but in unreported regressions do not find this to be the case.

7. Conclusions

The pandemic crisis offers a unique opportunity to study the significance of input-output linkages in the propagation of shocks. The pandemic came as a surprise and undoubtedly be seen an exogenous shock to the network of suppliers and customers of firms that otherwise are shaped endogenously based on managerial choices, firm performance, and market conditions.

Our analysis shows that both the direct effects of social distancing and its indirect effects through input-output linkages are quantitatively important drivers of stock prices during the outbreak of the pandemic. Our estimates imply that a one standard deviation increase in Distancing (the direct effect) is associated with a decline in stock returns of 2.7%, while a one standard deviation increase in Affected-sold (the indirect effect) is associated with a decline in stock returns of 3.1%. The indirect effect of social distancing from the sale of products to other firms is therefore estimated to be quantitatively at least as important as the direct effect from social distancing.

The average sector is highly sensitive to social distancing and relies substantially on its network of suppliers and customers to produce and sell its goods. These results are therefore also significant from an aggregate point of view.

Our results also show that larger firms and firms with deeper cash pockets are better able to deal with the effects of social distancing and the associated disruptions to a firm's network of suppliers and customers. These results point to the significance of liquidity support measures from governments and central banks to alleviate liquidity shortages.

Our results imply that the imposition of social distancing policies imposes large negative externalities on firms that rely on affected industries for the sale and purchase of intermediate products. Policymakers should be aware of these externalities as they weigh the inherently difficult tradeoff between saving lives and protecting the economy.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016), "Networks and the Macroeconomy: An Empirical Exploration." NBER Macroeconomics Annual 30 (1), 273–335.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2012), "The Network Origins of Aggregate Fluctuations," Econometrica 80, 1977–2016.

Alfaro, Laura, Anusha Chari, Andrew N. Greenland, and Peter K. Schott (2020), "Aggregate and Firm-Level Stock Returns during Pandemics, in Real Time," NBER working paper No. 26950.

Almeida, Heitor, Murillo Campello, and Michael S. Weisbach (2004), "The Cash Flow Sensitivity of Cash," *Journal of Finance* 59, 1777–1804.

Autor, David H. and David Dorn, 2013, "The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market," American Economic Review 103(5), 1553–1597.

Baqaee, David, and Emmanuel Farhi (2020a), "Nonlinear Production Networks with an Application to the Covid-19 crisis," Mimeo, Harvard University.

Baqaee, David, and Emmanuel Farhi (2020b), "Productivity and Misallocation in General Equilibrium," Quarterly Journal of Economics. Forthcoming.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis (2020), "COVID-19 Is Also a Reallocation Shock," NBER Working Paper No. 27137, May.

Barrot, Jean-Noël, and Julien Sauvagnat (2016), "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," Quarterly Journal of Economics 131 (3), 1543–92.

Bates, Thomas W., Kathleen M. Kahle, and René M. Stulz, 2009, "Why Do U.S. Firms Hold So Much More Cash than They Used to?," Journal of Finance 64, 1985–2021.

Bigio, Saki, and Jennifer La'O (2016), "Financial Frictions in Production Networks," NBER Working Paper 22212.

Chaney, Thomas, David Sraer, and David Thesmar (2012), "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment," American Economic Review 102 (6), 2381–2409.

Chodorow-Reich, G. (2014), "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008–9 Financial Crisis," Quarterly Journal of Economics, 129(1), 1–59.

CISA (2020), "Advisory Memorandum on Identification of Essential Critical Infrastructure Workers During Covid-19 Response," Memo, May 19. Available at: https://www.cisa.gov/sites/default/files/publications/Version_3.1_CISA_Guidance_on_Essential_Critical_Infrastructure_Workers.pdf

Di Giovanni, Julian, Andrei A. Levchenko, and Isabelle Mejean (2014), ''Firms, Destinations, and Aggregate Fluctuations,'' Econometrica 82, 1303–1340.

Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie (2020), "Corporate Immunity to the COVID-19 Pandemic," mimeo, Haas School of Business at University of California, Berkeley.

Dingel, Jonathan, and Brent Neiman (2020), "How Many Jobs Can Be Done at Home?", mimeo, Journal of Public Economics, forthcoming.

Eichenbaum, Martin, Sergio Rebelo, and Mathias Trabandt (2020), "The Macroeconomics of Epidemics," mimeo, Northwestern University. https://www.kellogg.northwestern.edu/faculty/rebelo/htm/epidemics.pdf

Fama, Eugene and Kenneth French (1992), "The Cross-Section of Expected Stock Returns," Journal of Finance 47, 427-465.

Gilje, Erik P., Elena Loutskina, and Philip E. Strahan (2016), "Exporting Liquidity: Branch Banking and Financial Integration," Journal of Finance 71(3), 1159–84.

Giroud, Xavier, and Holger M. Mueller (2017), "Firm leverage, Consumer Demand, and Employment Losses during the Great Recession," Quarterly Journal of Economics 132, 271–316.

Giroud, Xavier, and Holger M. Mueller (2019), "Firms' Internal Networks and Local Economic Shocks," American Economic Review 109(10), 3617–49.

Gormsen, Niels Joachim and Ralph S. J. Koijen (2020), "Coronavirus: Impact on Stock Prices and Growth Expectations," University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-22.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Ivan Werning (2020), "Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?" Mimeo, University of Chicago.

Glover, Andrew, Jonathan Heathcote, Dirk Krueger, and José-Víctor Ríos-Rull (2020), "Health versus Wealth: On the Distributional Effects of Controlling a Pandemic," mimeo, University of Pennsylvania. https://web.sas.upenn.edu/dkrueger/files/2020/04/adjvap22.pdf

Harford, Jarrad (1999), "Corporate Cash Reserves and Acquisitions," Journal of Finance 54, 1969–1997.

Hertzel, Michael G., Zhi Li, Micah S. Officer, and Kimberly J. Rodgers (2008), "Inter-Firm Linkages and the Wealth Effects of Financial Distress along the Supply Chain," Journal of Financial Economics 87, 374–387.

Ivashina, Victoria and David Scharfstein (2010), "Bank Lending During the Financial Crisis of 2008," Journal of Financial Economics, 97(3), 319-338.

Khwaja, Asim Ijaz and Atif Mian (2008), "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," American Economic Review 98(4), 1413–1442.

Kóren, Miklos and Rita Petö (2020), "Business disruptions from social distancing," mimeo, Central European University, March.

Landier, Augustin and David Thesmar (2020), "Earnings Expectations in the COVID Crisis," mimeo, MIT.

Leibovici, Fernando, Ana Maria Santacreu, and Matthew Famiglietti (2020), "How the Impact of Social Distancing Ripples through the Economy," St. Louis Fed On the Economy Blog, April 7, 2020. https://www.stlouisfed.org/on-the-economy/2020/april/impact-social-distancing-ripples-economy

Leontief, Wassily W. (1936), "Quantitative Input-Output Relations in the Economic System of the United States," Review of Economics and Statistics 18(3), 105–125.

Long, John B., and Charles I. Plosser (1983), "Real Business Cycles," Journal of Political Economy 91, 39–69.

Lustgarten, Steven H. (1975), "The Impact of Buyer Concentration in Manufacturing Industries," The Review of Economics and Statistics 57(2), 125–132.

Pagano, Marco, Christian Wagner and Josef Zechner (2020), "Disaster Resilience and Asset Prices," CEPR Discussion Paper 14773.

Ramelli, Stefano and Alexander Wagner (2020), "Feverish Stock Price Reactions to COVID-19," CEPR Discussion Paper 14511.

Stigler, George J. (1964), "A Theory of Oligopoly," Journal of Political Economy 72(1), 44–61.

Young, Jeffrey, Thomas F. Howells, Erich H. Strassner, and David B. Wasshausen (2015), "Supply-Use Tables for the United States," Survey 95, Bureau of Economic Analysis (BEA), September.

Table 1. Stock returns during the Covid-19 outbreak, by industry

This table reports firm stock returns over the first three months of 2020, averaged at the two-digit NAICS sector level. Sector 55 (Management of Companies and Enterprises) and sector 92 (Public Administration) are excluded from the table because there are no publicly listed firms from these sectors in our dataset.

Sector	Stock return
Sector 11: Agriculture, Forestry, Fishing and Hunting	-13.7%
Sector 21: Mining, Quarrying, and Oil and Gas Extraction	-53.4%
Sector 22: Utilities	-17.0%
Sector 23: Construction	-32.4%
Sector 31-33: Manufacturing	-15.3%
Sector 42: Wholesale Trade	-27.9%
Sector 44-45: Retail Trade	-31.3%
Sector 48-49: Transportation and Warehousing	-37.0%
Sector 51: Information	-17.4%
Sector 52: Finance and Insurance	-32.9%
Sector 53: Real Estate and Rental and Leasing	-34.3%
Sector 54: Professional, Scientific, and Technical Services	-24.8%
Sector 56: Administrative, Support and Waste Management	-35.6%
Sector 61: Educational Services	-29.5%
Sector 62: Health Care and Social Assistance	-14.9%
Sector 71: Arts, Entertainment, and Recreation	-45.2%
Sector 72: Accommodation and Food Services	-45.7%
Sector 81: Other Services (except Public Administration)	-33.6%
Total	-25.6%

Table 2. Descriptive statistics

Return is the stock return over the first three months of 2020. Return4 is the stock return over the first four months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. Lockdown equals one if the state governor has issued a statewide lockdown as of April 2020, and zero otherwise. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Non-essential equals one if CISA considers the industry to be nonessential, and zero otherwise. Total-sold is the fraction of total production sold to other industries. Total-intermediate is the fraction of total output consisting of intermediate products from other industries. Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. Affected-sold (nonessential) is the fraction of total production sold to nonessential industries. Affected-intermediate (nonessential) is the fraction of total output consisting of intermediate products from nonessential industries.

Variable	Obs	Mean	Std. Dev.	P25	P75	Min	Max
Firm-level							
Return	3,274	-0.256	0.490	-0.462	-0.153	-0.863	5.308
Return4	3,263	-0.117	0.754	-0.379	-0.051	-0.862	8.862
Book/Market	3,274	0.451	1.053	0.171	0.811	-6.764	3.592
Size	3,274	6.425	2.422	4.812	8.076	-3.892	13.733
Cash	3,274	0.217	0.277	0.027	0.300	0.000	1.000
Leverage	3,274	0.350	0.556	0.070	0.457	0.000	5.000
State-level							
Cases/Pop	50	42.884	61.957	15.800	37.800	8.900	389.600
Deaths/Pop	50	0.914	1.421	0.200	0.800	0.000	8.000
Lockdown	50	0.860	0.351	1.000	1.000	0.000	1.000
Industry-level							
Distancing	212	0.371	0.184	0.210	0.500	0.130	0.910
Non-essential	216	0.176	0.382	0.000	0.000	0.000	1.000
Total-sold	216	0.103	0.126	0.032	0.139	0.000	0.844
Total-intermediate	216	0.480	0.167	0.369	0.590	0.000	0.879
Affected-sold	216	0.027	0.041	0.005	0.031	0.000	0.264
Affected-intermediate	216	0.140	0.044	0.111	0.167	0.000	0.272
Affected-sold (nonessential)	216	0.019	0.062	0.000	0.005	0.000	0.548
Affected-intermediate (nonessential)	216	0.070	0.057	0.024	0.105	0.000	0.443

Table 3. Correlation matrix

Return is the stock return over the first three months of 2020. Return4 is the stock return over the first four months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. Lockdown equals one if the state governor has issued a statewide lockdown as of April 2020, and zero otherwise. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Non-essential equals one if CISA considers the industry to be nonessential, and zero otherwise. Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing.

	Return	Return4	Book/ Market	Size	Cash	Leverage	Cases/pop	Deaths/pop	Lockdown	Distancing	Nonessential	Affected-sold
Return4	0.89											
Book/Market	-0.19	-0.16										
Size	-0.19	-0.19	0.10									
Cash	0.21	0.22	-0.12	-0.23								
Leverage	0.06	0.06	-0.44	-0.15	-0.09							
Cases/pop	0.01	0.00	0.01	0.00	0.04	0.01						
Deaths/pop	0.02	0.00	0.00	0.00	0.04	0.01	0.98					
Lockdown	0.00	0.00	-0.02	0.02	0.05	0.01	0.09	0.09				
Distancing	-0.14	-0.16	0.15	0.08	-0.43	-0.03	-0.04	-0.04	-0.04			
Non-essential	-0.02	-0.01	-0.05	0.09	-0.06	0.09	0.04	0.04	0.05	0.14		
Affected-sold	-0.09	-0.09	0.07	-0.03	-0.20	0.00	0.02	0.02	0.01	0.25	-0.07	
Affected-intermediate	-0.04	-0.03	0.04	0.06	-0.10	0.01	-0.04	-0.04	-0.03	-0.05	-0.16	0.12

Table 4. Stock returns and firm characteristics during the pandemic outbreak

The dependent variable is the firm's total stock return over the first three months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. Lockdown equals one if the state governor has issued a statewide lockdown as of April 2020, and zero otherwise. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Non-essential equals one if CISA considers the industry to be nonessential, and zero otherwise. Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Baseline model	(2) Baseline model	(3) Baseline model
Book/Market	-0.0780***	-0.0706***	-0.0734***
	(0.0186)	(0.0184)	(0.0215)
Size	-0.0343***	-0.0270***	-0.0274***
	(0.00607)	(0.00607)	(0.00598)
Cash		0.284***	0.280***
		(0.0269)	(0.0302)
Leverage			-0.0116
			(0.0352)
Constant	0.000271	-0.112**	-0.103*
	(0.0556)	(0.0539)	(0.0556)
Observations	3,274	3,274	3,274
R-squared	0.063	0.087	0.087

Table 5. Stock returns during the pandemic and state shocks

The dependent variable is the firm's total stock return over the first three months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. Lockdown equals one if the state governor has issued a statewide lockdown as of April 2020, and zero otherwise. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Non-essential equals one if CISA considers the industry to be nonessential, and zero otherwise. Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. Column (4) includes state fixed effects. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) State shocks	(2) State shocks	(3) State shocks	(4) State shocks
Book/Market	-0.0707***	-0.0707***	-0.0707***	-0.0679***
	(0.0185)	(0.0185)	(0.0185)	(0.0184)
Size	-0.0271***	-0.0271***	-0.0270***	-0.0286***
	(0.00606)	(0.00605)	(0.00604)	(0.00620)
Cash	0.284***	0.283***	0.284***	0.230***
	(0.0270)	(0.0271)	(0.0275)	(0.0365)
Cases/Pop	2.31e-05		2.63e-05	
	(8.77e-05)		(8.86e-05)	
Deaths/Pop		0.00189		
		(0.00441)		
Lockdown			-0.0226	
			(0.0874)	
Constant	-0.113**	-0.114**	-0.0920	
	(0.0553)	(0.0551)	(0.101)	
State fixed effects	No	No	No	Yes
Observations	3,274	3,274	3,274	3,274
R-squared	0.087	0.087	0.087	0.109

Table 6. Stock returns during the pandemic and industry exposure

The dependent variable is the firm's total stock return over the first three months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. Lockdown equals one if the state governor has issued a statewide lockdown as of April 2020, and zero otherwise. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Total-sold is the fraction of total production sold to other industries. Total-intermediate is the fraction of total output consisting of intermediate products from other industries. Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Industry exposures	(2) Industry exposures	(3) Industry exposures	(4) Industry exposures	(5) Industry exposures
Book/Market	-0.0670***	-0.0670***	-0.0671***	-0.0661***	-0.0668***
	(0.0187)	(0.0187)	(0.0187)	(0.0186)	(0.0187)
Size	-0.0272***	-0.0273***	-0.0273***	-0.0281***	-0.0272***
	(0.00604)	(0.00606)	(0.00605)	(0.00608)	(0.00605)
Cash	0.245***	0.243***	0.246***	0.232***	0.242***
	(0.0282)	(0.0289)	(0.0277)	(0.0292)	(0.0278)
Cases/Pop	6.47e-05	6.64e-05	6.84e-05	7.68e-05	6.16e-05
	(7.32e-05)	(7.28e-05)	(7.15e-05)	(7.33e-05)	(7.34e-05)
Distancing	-0.148***	-0.147***	-0.137**	-0.116**	-0.153***
	(0.0539)	(0.0531)	(0.0537)	(0.0507)	(0.0527)
Total-sold		-0.0362			
		(0.0703)			
Total-intermediate			0.0372		
			(0.0575)		
Affected-sold				-0.774***	
				(0.193)	
Affected-intermediate					-0.149
					(0.168)
Constant	-0.0552	-0.0513	-0.0753	-0.0370	-0.0348
	(0.0651)	(0.0681)	(0.0663)	(0.0663)	(0.0667)
Observations	3,226	3,226	3,226	3,226	3,226
R-squared	0.087	0.088	0.088	0.090	0.088

Table 7. Stock returns during the pandemic and interactions between state shocks and industry exposures

The dependent variable is the firm's total stock return over the first three months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. All regressions include state and industry fixed effects. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Interactions between state shocks and industry exposures	(2) Interactions between state shocks and industry exposures	(3) Interactions between state shocks and industry exposures
Book/Market	-0.0552***	-0.0553***	-0.0557***
	(0.0188)	(0.0188)	(0.0188)
Size	-0.0339***	-0.0339***	-0.0340***
	(0.00642)	(0.00636)	(0.00636)
Cash	0.00873	0.0122	0.0133
	(0.0552)	(0.0546)	(0.0547)
Cases/Pop × Distancing	0.000381		
	(0.000370)		
Cases/Pop × Affected-sold		0.00117	
		(0.000976)	
Cases/Pop × Affected-intermediate			0.00233**
			(0.00115)
State fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	3,226	3,274	3,274
R-squared	0.178	0.181	0.181

Table 8. Stock returns during the pandemic and interactions between industry exposures and firm characteristics

The dependent variable is the firm's total stock return over the first three months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Leverage is the ratio of total debt to total assets, winsorized at the 99th percentile. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. All regressions include state and industry fixed effects. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Industry exposures and firm characteristics	(2) Industry exposures and firm characteristics	(3) Industry exposures and firm characteristics
Book/Market	-0.0957***	-0.0593**	-0.0873**
	(0.0350)	(0.0243)	(0.0355)
Size	-0.0553***	-0.0395***	-0.0363***
	(0.0115)	(0.00791)	(0.0136)
Cash	-0.121	-0.00564	-0.0600
	(0.0866)	(0.0676)	(0.153)
Book/market × Distancing	0.132*		
	(0.0709)		
Size × Distancing	0.0709***		
	(0.0247)		
Cash × Distancing	0.506**		
	(0.233)		
Book/market × Affected-sold		0.155	
		(0.218)	
Size × Affected-sold		0.205**	
		(0.0940)	
Cash × Affected-sold		0.765	
		(1.199)	
Book/market × Affected-intermediate			0.259
			(0.282)
Size × Affected-intermediate			0.0223
			(0.116)
Cash × Affected-intermediate			0.603
			(1.093)
State fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	3,226	3,274	3,274
R-squared	0.182	0.182	0.181

Table 9. Robustness check: Stock returns including April

The dependent variable is the firm's total stock return over the first four months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing. Columns (4) and (5) include state and industry fixed effects. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Book/Market	-0.0802**	-0.0789**	-0.0802**	-0.0662	-0.130
	(0.0322)	(0.0321)	(0.0322)	(0.0428)	(0.0802)
Size	-0.0432***	-0.0444***	-0.0432***	-0.0640***	-0.0686***
	(0.0102)	(0.0103)	(0.0101)	(0.0139)	(0.0215)
Cash	0.406***	0.388***	0.406***	0.0334	0.0940
	(0.0435)	(0.0445)	(0.0438)	(0.104)	(0.268)
Cases/pop	2.12e-05	3.81e-05	2.16e-05		
	(0.000105)	(0.000106)	(0.000105)		
Distancing	-0.292***	-0.247***	-0.292***		
	(0.0747)	(0.0692)	(0.0760)		
Affected-sold		-1.079***			
		(0.272)			
Affected-intermediate			0.0203		
			(0.242)		
Book/Market × Affected-sold				0.239	
				(0.358)	
Size × Affected-sold				0.476***	
				(0.163)	
Cash × Affected-sold				2.041	
				(2.075)	
Book/Market × Affected-intermediate					0.569
					(0.531)
Size × Affected-intermediate					0.149
					(0.158)
Cash × Affected-intermediate					-0.103
					(1.883)
Constant	0.210**	0.235**	0.207*		
	(0.102)	(0.104)	(0.111)		
State fixed effects	No	No	No	Yes	Yes
Industry fixed effects	No	No	No	Yes	Yes
Observations	3,215	3,215	3,215	3,263	3,263
R-squared	0.086	0.089	0.086	0.148	0.147

Table 10. Robustness check: Nonessential industries

The dependent variable is the firm's total stock return over the first three months of 2020. Book/market is the book-to-market value of the firm's stock. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash and cash equivalents to total assets. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Non-essential equals one if CISA considers the industry to be nonessential, and zero otherwise. Affected-sold (nonessential) is the fraction of total production sold to nonessential industries. Affected-intermediate (nonessential) is the fraction of total output consisting of intermediate products from nonessential industries. Standard errors are adjusted for clustering at the state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)
Book/market	-0.0708***	-0.0709***	-0.0708***
	(0.0184)	(0.0184)	(0.0184)
Size	-0.0270***	-0.0272***	-0.0270***
	(0.00603)	(0.00602)	(0.00597)
Cash	0.283***	0.276***	0.284***
	(0.0275)	(0.0282)	(0.0280)
Cases/Pop	2.41e-05	2.47e-05	2.36e-05
	(8.69e-05)	(8.87e-05)	(8.75e-05)
Nonessential	-0.00683	-0.00144	-0.00891
	(0.0258)	(0.0253)	(0.0246)
Affected-sold (nonessential)		-0.365***	
		(0.0966)	
Affected-intermediate (nonessential)			0.0626
			(0.143)
Constant	-0.113**	-0.106*	-0.116*
	(0.0558)	(0.0564)	(0.0597)
Observations	3,274	3,274	3,274
R-squared	0.087	0.088	0.087

Appendix Table 1. Sector level variables: Social distancing and input-output linkages

This table reports industry-level social distancing and input-output linkages variables at the 2-digit NAICS sector level. In the analysis we use these variables at the four-digit NAICS level. Sector indicates the names of the two-digit NAICS sector name. NAICS indicates the four-digit NAICS codes that make up the sector. Distancing is the share of industry employment affected by social distancing from Kóren and Petö (2020). Non-essential equals one if CISA considers the industry to be nonessential, and zero otherwise. Total-sold is the fraction of total production sold to other industries. Total-intermediate is the fraction of total output consisting of intermediate products from other industries. Affected-sold is the fraction of total production sold to industries affected by social distancing. Affected-intermediate is the fraction of total output consisting of intermediate products from industries affected by social distancing.

Sector	NAICS	Distancing	Non-essential	Total-sold	Total-intermediate	Affected-sold	Affected-intermediate
Agriculture, Forestry, Fishing and Hunting	1111-1153	0.29	0.00	0.05	0.42	0.00	0.13
Mining, Quarrying, Oil and Gas	2111-2131	0.46	0.00	0.09	0.44	0.04	0.14
Utilities	2211-2213	0.46	0.00	0.27	0.41	0.01	0.14
Construction	2361-2389	0.38	0.00	0.09	0.46	0.04	0.12
Manufacturing	3111-3399	0.20	0.00	0.06	0.50	0.01	0.12
Wholesale Trade	4231-4251	0.31	0.05	0.06	0.46	0.02	0.15
Retail Trade	4411-4543	0.65	0.38	0.03	0.30	0.01	0.10
Transportation and Warehousing	4811-4931	0.54	0.00	0.06	0.46	0.02	0.14
Information	5111-5191	0.27	0.60	0.18	0.51	0.04	0.17
Finance and Insurance	5211-5259	0.44	0.00	0.13	0.38	0.05	0.12
Real Estate, Rental and Leasing	5311-5331	0.50	0.91	0.05	0.22	0.02	0.08
Professional, Scientific and Technical Services	5411-5419	0.23	0.16	0.34	0.33	0.08	0.11
Administration, Support and Waste Mgt	5611-5629	0.41	0.33	0.07	0.41	0.01	0.14
Educational Services	6111-6117	0.38	1.00	0.30	0.22	0.01	0.08
Health Care and Social Assistance	6211-6244	0.66	0.02	0.07	0.38	0.01	0.13
Arts, Entertainment, and Recreation	7111-7139	0.42	1.00	0.33	0.35	0.08	0.11
Accommodation and Food Services	7211-7225	0.50	0.39	0.18	0.50	0.07	0.17
Other Services	8111-8141	0.56	0.43	0.11	0.32	0.06	0.11
Total		0.34	0.15	0.10	0.43	0.03	0.12

Appendix Table 2. State level variables: Virus cases and lockdowns

This table reports state-level health statistics and lockdown measures. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000s. Lockdown equals one if the state governor has issued a statewide lockdown as of early April 2020, and zero otherwise.

State	Cases/pop	Deaths/pop	Lockdown
Alabama	20.0	0.3	Yes
Alaska	16.3	0.4	Yes
Arizona	17.7	0.3	Yes
Arkansas	17.3	0.3	No
California	18.9	0.4	Yes
Colorado	45.6	0.9	Yes
Connecticut	87.7	1.9	Yes
Delaware	32.8	1.0	Yes
District of Columbia	70.1	1.3	Yes
Florida	29.5	0.4	Yes
Georgia	37.0	1.0	Yes
Hawaii	14.4	0.0	Yes
Idaho	23.2	0.4	Yes
Illinois	47.3	0.8	Yes
Indiana	32.1	0.7	Yes
Iowa	15.8	0.2	No
Kansas	14.7	0.3	Yes
Kentucky	10.7	0.2	Yes
Louisiana	112.7	5.1	Yes
Maine	22.5	0.4	Yes
Maryland	27.5	0.3	Yes
Massachusetts	94.6	2.2	Yes
Michigan	118.9	2.6	Yes
Minnesota	11.2	0.2	Yes
Mississippi	31.5	0.7	Yes
Missouri	21.6	0.2	Yes
Montana	17.2	0.4	Yes
Nebraska	8.9	0.2	No
Nevada	36.1	0.6	Yes
New Hampshire	23.1	0.2	Yes
New Jersey	210.5	3.0	Yes
New Mexico	13.4	0.2	Yes
New York	389.6	8.0	Yes
North Carolina	14.3	0.1	Yes
North Dakota	16.5	0.4	No
Ohio	18.8	0.5	Yes
Oklahoma	14.3	0.6	No
Oregon	16.4	0.4	Yes
Pennsylvania	37.8	0.5	Yes
Rhode Island	46.2	0.8	Yes
South Carolina	21.0	0.4	Yes
South Dakota	12.2	0.1	No
Tennessee	32.8	0.3	Yes
Texas	11.3	0.1	Yes
Utah	27.7	0.2	No
Vermont	47.0	2.1	Yes
Virginia	14.6	0.3	Yes
Washington	90.7	3.4	Yes
West Virginia	9.0	0.1	Yes
Wisconsin	23.2	0.3	Yes