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Pandemics, intermediate goods, and corporate valuation

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We evaluate whether the changes in valuation of U.S. corporates during the first wave of the COVID-19 pandemic depend on their downstream or upstream industries' exposure to social distancing. Using a new dataset on sectoral dependence on the use and sale of intermediate goods, we find that firms whose downstream sectors are more affected by social distancing suffer from a greater decline in stock prices during the first quarter of 2020. Such an effect is mitigated for large firms.

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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., Acemoglu et al., 2012; Carvalho et al., 2021; Hertzel et al., 2008; Long and Plosser, 1983). 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 (“upstream” exposure) and sale (“downstream” exposure) of intermediate goods, using input–output...
tables from the U.S. Bureau of Economic Analysis. We combine this data 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. We focus on asset price changes as outcome variable because they have the advantage that they are forward-looking. The changes in stock prices capture the combined effect of changes in cash flows and changes in discounting of returns over time.

As is standard in empirical 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 et al., 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. While the spread of the pandemic continued in subsequent quarters, focusing on the immediate impact of the pandemic has the advantage that the pandemic can be treated as an exogenous shock, enhancing identification. Moreover, stock prices are forward looking and therefore incorporate the market’s expectation of the evolution of the pandemic and associated policy responses.

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 2.4%, 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 2.7%. 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.

These findings are robust to a number of robustness tests and extensions, including: (i) accounting for the firm’s international exposure to China and global value chains, (ii) considering the interaction between social distancing and lockdown policies, (iii) accounting for the ease with which workers in the firm’s sector can work from home, and (iv) extending the horizon over which stock returns are computed.

Our paper is related to ongoing research on the nature of the COVID-19 shock and its transmission to the real economy. In the macro literature, a key research question is whether the COVID-19 crisis should be regarded primarily as a supply or a demand shock. 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. We contribute to this literature by showing that disruptions in the supply side of the production chain magnify the initial supply shock and that this effect is heterogeneous across sectors.

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.
Baqae 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. Baqae 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. Relatedly, Bonadio, Hsu, Levchenko, and Pandalei–Nayar (2020) using a quantitative model show that global value chains have been an important transmission channel of foreign lockdowns.

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.

Relatedly, there is ongoing empirical research studying the impact of Covid-19 spread and containment policies on economic activity (e.g., Caselli et al., 2020; Demirguc-Kunt et al., 2020; and Famiglietti and Leibovici, 2021). A key challenge in this research is that the virus spread and associated policies interact with each other. A key difference with these papers is our focus on stock prices and the use of firm–level data as opposed to aggregate macroeconomic data, which allows to get closer to the underlying channels of the effects of containment policies and thus enhance identification.

Research is also exploring how firms’ earnings forecasts and stock prices have been affected by the shock. For instance, Gomme and Kojien (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. Similarly, Betscher et al. (2020) find that stock prices of U.S. firms react negatively to the outbreak of COVID-19 cases in the county where the firm is headquartered. Chen et al. (2020) find that stock prices reacted favorably to lockdown announcements. 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. In a closely related paper, Ding et al. (2020) 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. While they also consider the role of input–output linkages, a key difference with our paper is that they do not consider the impact of social distancing and its interaction with lockdown policies. To the best of our knowledge, ours is the first paper to simultaneously consider the combined influence of social distancing and input–output linkages on the stock performance of firms, and their interactions with lockdown policies, with a special focus on how financial shocks that initially mainly impact one set of firms can be transmitted to other firms through input–output linkages.

More generally, 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). 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) and networks of suppliers and customers (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016; Cohen and Frazzini, 2008; Menzly and Ozbos, 2010; Bigio and LaO, 2016; Di Giovanni et al., 2014; Baqae and Farhi, 2020). 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.

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:

\[
    x_i = a_{i1}x_1 + a_{i2}x_2 + ... + a_{in}x_n + d_i \tag{1}
\]

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:

\[
    x = (I - A)^{-1}d \tag{3}
\]

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 et al. (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:

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

Let \( s \) be the vector of the fraction of output that is lost because of social distancing. We can then rewrite Eq. (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 and US headquartered 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. Either way, stock prices over this period were influenced by interventions by the Federal Reserve, which helped calm financial markets, and mitigated the effects of lockdowns and health shocks on stock prices. Our estimates should therefore be seen as lower bounds compared to the effects in the absence of these interventions.

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 2017 NAICS level.

Following Ramelli and Wagner (2020), we also control for a firm’s international exposure using data from Hoberg and Moon (2019) on a firm’s perception of exposure of its activities to China. China not only plays a key role in the global value chain for many U.S. firms but it is also the country where the pandemic first broke out. Moreover, there was heightened risk of a trade war between the U.S. and China during our sample period. It is therefore likely that share prices of U.S. firms are sensitive to exposure to China. China is a dummy variable equal to one if firms disclosed in their 10-K statements of 2017 that they had offshore activities with China, either via importing (inputs), exporting (outputs), or both. This measure is available for only a subset of the firms in our sample. As an alternative measure of a firm’s international exposure we create a sector-level variable which captures the importance of global value chains through the import content of the exports of the sector the firm operates in. Specifically, we compute the Import content variable as the weighted average import content of the sector’s exports, weighted across destination countries according to the total exports of the sector to the destination country and the index of lockdown restrictions in the destination country. We obtain information on the import content of the exports of the sector from the 2018 version of the OECD STAN bilateral input–output database (downloaded from https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4_2018) and we use the Oxford restrictions index in the export destination country developed and maintained by Hale et al. (2020). We then match the sector-level import content variable, computed at the ISIC Rev. 4 level, to the 2017 NAICS sector the firm is active in using an ISIC-NAICS concordance table obtained from the US Census (available at https://www.census.gov/eos/www/naics/concordances/concordances.html).

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. Statewide lockdowns were announced by governors in staggered fashion. Because lockdowns may have been largely anticipated, and the adoption of lockdown in one state is unlikely to be independent of that of other states, we do not use the exact announcement date of the lockdown but instead distinguish more broadly between states that were early adopters of lockdowns, states that were late adopters of lockdowns, and states that never declared a lockdown. Early Lockdown equals one if the state governor issued a statewide lockdown before Friday March 27, 2020, and zero otherwise. Late Lockdown equals one if the state governor issued a statewide lockdown on or after Friday March 27, 2020, and zero otherwise. We also construct an aggregate indicator Lockdown which equals one if the state governor issued a statewide lockdown by mid-April 2020. Lockdown is simply the sum of the Early lockdown and Late lockdown variables. Information on announced statewide lockdowns is obtained from the NBC News website (https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736) and the references therein to the official announcement on each state governor’s website. This data has previously been used by Chen et al., 2020.

We also include information on the sensitivity of industries to lockdown and social distancing measures and the spread of COVID-19. Distancing is the share of industry employment affected by social distancing from Kören et al., 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). The measure captures both the demand and supply effects of social distancing. On the supply side, firms with working conditions that involve physical proximity with co-workers might choose to shut down production in order to

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1. Our measure of foreign exposure is comparable to the global value chain intensity measure of Santacreu et al. (2021). An important difference is that the latter is computed only for the manufacturing sector. The correlation between the two measures for the sub-set of manufacturing industries is high at 64.4%.
reduce contact rates and curb the dissemination of the virus. On the demand side, customers might stay away from contact-intensive firms because they do not want to interact with potentially infected workers.

Non-essential is a variable that indicates whether the Cybersecurity and Infrastructure Security Agency (CISA) of the Department of Homeland Security considers that the industry is 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.

Since lockdown policies and social distancing will interact to impact firms, and indeed may reinforce each other, our empirical analysis will also consider interactions between the two variables. In addition, we construct a variable Nonessential-distancing that considers the combination of the two variables by taking a value of one if CISA considers the industry to be nonessential and/or the industry is strongly affected by social distancing (i.e., if the social distancing affected share is equal to above the median of 37.5%), and zero otherwise.

Similarly, we consider interactions between COVID-19 spread (Cases/pop) and social distancing.

Moreover, since many firms in the sample operate in multiple states and sell their goods nationwide, the impact of COVID-19 spread on firms may be more at the sectoral level rather than the state level. We therefore construct an industry-based measure of spread, Cases/pop industry, which is the weighted average of Cases/pop, weighted across states by the sector’s contribution to real GDP in the state. We obtain data on real GDP (in millions of chained 2012 dollars) at the sector-state level from the BEA’s regional accounts (Table SQGDP9, available from https://www.bea.gov/data/gdp/gdp-state).

While the focus of our analysis is on the impact of social distancing and lockdown policies, the pandemic may have also differentially impacted firms depending on the ease with which employees can work from home. We create a variable, Working from home, which is the share of the industry’s jobs that can be done at home. We collect this information from Table 3 in Dingel and Neiman (2020), who compute this share at the two-digit NAICS level using data on occupations that can be done at home from O*Net and data on the occupational composition in each sector’s employment from the 2018 Occupational Employment Statistics of the US Bureau of Labor Statistics. We use the unweighted version of their index.

Table 3 in Dingel and Neiman (2020) considers the proportion of jobs that can be done from home. To the extent that jobs can be done from home, workers will be able to maintain productivity while working from home. The two measures therefore capture slightly different dimensions of the effect of lockdown policies. While both measures consider the impact of such policies on whether the job requires physical presence (working at the office), the social distancing measure also captures the degree to which such lockdown policies affect the ability to work with others (teamwork) and interact with customers (customer contact).

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 Kören et al., 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 Kören et al., 2020.

Similarly, 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 are 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 are not designated as essential by CISA.

Moreover, we capture the combined impact of Non-essential and Social distancing via input–output linkages by computing Affected-sold (nonessential/distancing), which is the fraction of total production sold to nonessential/social distancing industries, and Affected-intermediate (nonessential/distancing), which is the fraction of total output consisting of intermediate products from nonessential/social distancing industries. Affected-sold (nonessential/distancing) is computed for a given sector by aggregating row entries from the supply table across only those columns of industries that are nonessential and/or strongly affected by social distancing (i.e., the variable Nonessential/distancing takes a value of one) while Affected-intermediate (nonessential/distancing) is computed for a given sector by aggregating row entries from the use table across only those columns of industries that nonessential and/or strongly affected by social distancing.
We merge all data at the four-digit NAICS level and use standard concordance tables from the US Census 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 by early April, the eight exceptions being Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, Utah, and Wyoming. (Oklahoma did issue a shelter in place for Oklahoma City and Tulsa but not a statewide lockdown). The first state to announce a statewide lockdown was California on March 19. By March 26, 24 out of 51 states had issued a nationwide lockdown, and by April 6, 19 other states had followed suit.

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.2 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 and transmission, and distribution (NAICS 2211) industry, which has a social distancing value of 46.0 percent. Table 2 also presents summary 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.

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2 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.
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 1% winsorized at each tail. 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. China equals one if the firm disclosed that it has input-offshoring and/or output-offshoring activities with China, and zero otherwise. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000 s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000 s. Distancing is the share of industry employment affected by social distancing from Kóren et al., 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 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 |
|----------|-----|------|-----------|-----|-----|-----|-----|
| 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% |

| 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 | −6.76 | 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 | 0.00 | 1.00 |
| Leverage | 3,274 | 0.350 | 0.556 | 0.070 | 0.457 | 0.00 | 5.00 |
| China | 2,339 | 0.531 | 0.499 | 0.000 | 1.000 | 0.00 | 1.000 |
| State-level |
| Cases/Pop | 50 | 42.9 | 62.0 | 15.8 | 37.8 | 8.9 | 389.6 |
| Deaths/Pop | 50 | 0.914 | 1.421 | 0.200 | 0.800 | 0.00 | 8.000 |
| Early lockdown | 50 | 0.588 | 0.492 | 0.000 | 1.000 | 0.00 | 1.000 |
| Late lockdown | 50 | 0.381 | 0.486 | 0.000 | 1.000 | 0.00 | 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 | 0.00 | 1.000 |
| Working from home | 216 | 0.330 | 0.207 | 0.220 | 0.420 | 0.040 | 0.830 |
| Cases/Pop industry | 216 | 60.5 | 16.4 | 47.7 | 68.0 | 21.4 | 106.7 |
| Import content | 216 | 0.128 | 0.055 | 0.074 | 0.166 | 0.038 | 0.302 |
| Total-sold | 216 | 0.103 | 0.126 | 0.032 | 0.139 | 0.000 | 0.844 |
| Total-intermediate | 216 | 0.840 | 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 |
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:

\[
\text{Return}_i = \alpha + \beta_1 \cdot \text{Firm traits}_i + \beta_2 \cdot \text{Infections and lockdowns}_k + \beta_3 \cdot \text{Affected industry}_j + \varepsilon_i
\]

where \(\text{Return}_i\) is the compounded stock return of firm \(i\) over the first quarter of 2020, \(\text{Firm traits}_i\) is a set of firm-level variables, \(\text{Infections and lockdowns}_k\) is a set of state-level variables, \(\text{Affected industry}_j\) is a set of industry-level variables, \(i\) denotes firm \(i\), \(j\) denotes industry \(j\), \(k\) denotes state \(k\), \(\alpha\) denotes a constant, and \(\varepsilon_i\) is the error term with the usual properties.

More specifically, \(\text{Firm traits} \in \{\text{BM, Size, Cash, Leverage}\}\) 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 \(\beta_1\) 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 et al., 2009), and we expect a negative coefficient \(\beta_1\) on the Leverage variable because highly levered firms may become financially constrained during the crisis (Giroud and Mueller, 2017).

\(\text{Infections and lockdowns} \in \{\text{Cases/Pop, Lockdown}\}\) 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 100,000 \(s\), 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 \(\beta_2\) on Cases/Pop because it reflects the depth of the health crisis and we expect a negative coefficient \(\beta_2\) 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.

\(\text{Affected industry} \in \{\text{Distancing, Total – sold, Total – intermediate, Affected – sold, Affected – intermediate}\}\) 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:

\[
\text{Return}_i = \alpha_i + \beta_4 \cdot \text{Firm traits}_i + \beta_2 \cdot \text{Infections and lockdowns}_k \cdot \text{Affected industry}_j + \varepsilon_i
\]
tions 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-19 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 Eq. (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. In our sample, none of these factors enters significantly.3 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. Prior work has shown that share prices during the pandemic are also influenced by a firm’s international exposure (e.g., Ramelli and Wagner (2020) and global value chains (e.g., Bonadio et al., 2020). While not the focus of our study, we therefore control for a firm’s exposure to China through either offshoring of inputs or outputs. The sample reduces to 2339 firms. The China exposure variable does not enter significantly. Similarly, in column (5) we control for the intensity of imports and exports of the sector and the firm operates in, scaled by the intensity of lockdown restrictions in export destination countries, to capture the impact of foreign lockdowns through global value chains. The import content variable enters with an unexpected positive sign, perhaps reflecting that exports offered an important shock absorber to some firms, despite foreign downs 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.

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

3 When including all variables simultaneously, results do not change.
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 99th percentile. China takes a value of one if the firm disclosed that it has input-offshoring and/or output-offshoring activities with China, and zero otherwise. 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. Stock returns and book-to-market values are winsorized at the 1st and 99th percentiles. Size is the logarithm of total assets.

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. Early lockdown equals one if the state governor has issued a statewide lockdown before March 27, 2020, and zero otherwise. Distancing is the share of industry employment affected by social distancing from Kóren et al., 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.

|            | Return4 | Book/market | Size | Cash | Leverage | Cases/pop | Deaths/pop | Early lockdown | Distancing | Nonessential | Affected-sold | Affected-intermediate |
|------------|---------|-------------|------|------|----------|-----------|------------|---------------|------------|--------------|--------------|-----------------------|
| Return4    | 0.89    | -0.19       | -0.16| 0.10 | 0.16     | 0.13      | 0.08       | 0.04          | -0.23      | -0.18         | -0.18        | -0.04                |
| Book/market| -0.19   | -0.16       | 0.10 | 0.13 | 0.18     | 0.10      | 0.09       | 0.03          | -0.23      | -0.18         | -0.18        | -0.04                |
| Size       | -0.19   | -0.16       | -0.12| -0.15| -0.09    | -0.15     | -0.09      | 0.01          | -0.14      | -0.16         | -0.16        | 0.14                 |
| Cash       | 0.21    | 0.22        | 0.12 | -0.15| -0.09    | 0.08      | -0.09      | 0.02          | 0.04       | 0.04          | 0.04         | 0.25                 |
| Leverage   | 0.06    | 0.06        | -0.44| -0.15| -0.09    | 0.08      | -0.09      | 0.02          | -0.04      | -0.04         | -0.04        | 0.25                 |
| Cases/pop  | 0.01    | 0.00        | 0.01 | 0.00 | 0.04     | 0.01      | 0.04       | 0.00          | 0.02       | 0.02          | 0.02         | 0.25                 |
| Deaths/pop | 0.02    | 0.00        | 0.00 | 0.00 | 0.04     | 0.01      | 0.04       | 0.00          | 0.00       | 0.00          | 0.00         | 0.25                 |
| Early lockdown | 0.08   | 0.06        | -0.01| 0.02 | 0.19     | -0.06     | 0.39       | 0.42          | 0.08       | 0.15          | 0.16         | 0.14                 |
| Distancing | -0.14   | -0.16       | 0.15 | 0.08 | -0.43    | -0.03     | -0.04      | -0.04         | -0.04      | -0.23         | -0.23        | 0.14                 |
| Non-essential | -0.02 | -0.02       | -0.05| 0.09 | -0.06    | -0.03     | -0.04      | -0.04         | -0.23      | -0.23         | -0.23        | 0.14                 |
| Affected-sold | -0.09 | -0.09       | 0.07 | 0.03 | 0.20     | 0.00      | 0.02       | 0.02          | 0.01       | 0.25          | 0.25         | -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 each tail. 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. China takes a value of one if the firm disclosed that it has input-offshoring and/or output-offshoring activities with China, and zero otherwise. Import content is the weighted average import content of the sector’s exports, weighted across destination countries by the total exports of the sector to the destination country and the index of lockdown restrictions in the destination country. All (continuous) explanatory variables are standardized. 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.

|            | Baseline model | Baseline model | Baseline model | Baseline model | Baseline model |
|------------|----------------|----------------|----------------|----------------|----------------|
| Book/Market| -0.0821***     | -0.0743***     | -0.0772***     | -0.0901***     | -0.0751***     |
|            | (0.0195)       | (0.0194)       | (0.0226)       | (0.0263)       | (0.0227)       |
| Size       | -0.0832***     | -0.0655***     | -0.0664***     | -0.0616***     | -0.0664***     |
|            | (0.0147)       | (0.0145)       | (0.0151)       | (0.0144)       | (0.0144)       |
| Cash       | 0.0788***      | 0.0776***      | 0.0790***      | 0.0645***      | 0.0645***      |
|            | (0.00746)      | (0.00836)      | (0.0141)       | (0.00778)      | (0.00778)      |
| Leverage   | -0.00648       | -0.00904       | -0.000984      | -0.00345       | -0.00345       |
|            | (0.0196)       | (0.0238)       | (0.0210)       |             |               |
| China      | -0.00812       | -0.00812       | -0.00812       | -0.00812       | -0.00812       |
|            | (0.0210)       | (0.0210)       | (0.0210)       |             |               |
| Import content | -0.256***    | -0.256***           | -0.256***     | -0.249***     | -0.256***     |
|            | (0.0201)       | (0.0131)       | (0.0130)       | (0.0156)       | (0.0113)       |
| Constant   | -0.256***      | -0.256***      | -0.256***      | -0.249***      | -0.256***      |
|            | (0.0201)       | (0.0131)       | (0.0130)       | (0.0156)       | (0.0113)       |
| Observations | 3274            | 3274            | 3274            | 2339           | 3274           |
| R-squared  | 0.063           | 0.087           | 0.087           | 0.106          | 0.092          |

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 2.7%, 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. This finding that input reliance is not that important in explaining negative stock price reactions is reminiscent of Hoberg and Moon (2019) who in a different context find that input offshoring can
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 1% winsorized at each tail. 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 100,000. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000. Lockdown equals one if the state governor has issued a statewide lockdown as of April 2020, and zero otherwise. Early (late) lockdown equals one if the state governor has issued a statewide lockdown before (on or after) March 27, 2020, and zero otherwise. Column (5) includes state fixed effects. All (continuous) explanatory variables are standardized. 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.

|                       | (1) State shocks | (2) State shocks | (3) State shocks | (4) State shocks | (5) State shocks |
|-----------------------|------------------|------------------|------------------|------------------|------------------|
| Book/Market           | −0.0744***       | −0.0744***       | −0.0745***       | −0.0746***       | −0.0715***       |
|                       | (0.0194)         | (0.0194)         | (0.0194)         | (0.0194)         | (0.0193)         |
| Size                  | −0.0655***       | −0.0655***       | −0.0654***       | −0.0670***       | −0.0694***       |
|                       | (0.0147)         | (0.0147)         | (0.0146)         | (0.0148)         | (0.0150)         |
| Cash                  | 0.0787***        | 0.0786***        | 0.0789***        | 0.0738***        | 0.0637***        |
|                       | (0.00749)        | (0.00752)        | (0.00762)        | (0.00844)        | (0.0101)         |
| Cases/Pop             | 0.00254          | 0.00289          | −0.00776         |                  |                  |
|                       | (0.00961)        | (0.00971)        | (0.01000)        |                  |                  |
| Deaths/Pop            | 0.00430          | 0.000289         | −0.00776         |                  |                  |
|                       | (0.0100)         | (0.00971)        | (0.01000)        |                  |                  |
| Lockdown              | −0.0226          |                  |                  |                  |                  |
|                       | (0.0874)         |                  |                  |                  |                  |
| Early lockdown        |                  |                  |                  |                  | 0.00767          |
|                       |                  |                  |                  |                  | (0.0889)         |
| Late lockdown         |                  |                  |                  |                  | −0.0506          |
|                       |                  |                  |                  |                  | (0.0887)         |
| Constant              | −0.256***        | −0.256***        | −0.234***        | −0.241***        |                  |
|                       | (0.0131)         | (0.0132)         | (0.0858)         | (0.0864)         |                  |
| State fixed effects   | No               | No               | No               | No               | Yes              |
| Observations          | 3,274            | 3,274            | 3,274            | 3,274            | 3,274            |
| R-squared             | 0.087            | 0.087            | 0.087            | 0.087            | 0.109            |

The results in Table 4 indicated that state-wide shocks related to COVID-19 spread do not explain variation in stock price performance for the firms in our sample. Since many firms in our sample are large firms that operate in multiple states and sell their goods nationwide, the impact of COVID-19 spread for the firms in our sample may be more at the sectoral level rather than the state level. To account for this possibility, in Column (6) of Table 6, we include Cases/Pop industry, which is the weighted average of Cases/pop, weighted across states by the sector’s contribution to real GDP in the state. This variable if anything indicates that the stock price of firms operating in sectors whose activity tends to be concentrated in states with a high number of reported COVID-19 cases was not adversely affected, although the coefficient is only borderline significant. This result, taken together with the results of Table 4, suggests that what matters for these firms that tend to operate nationally is the large systematic shock due to COVID-19 spread at national level.

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 a one standard deviation reduction in dependence on intermediate inputs when COVID-19 cases decrease by one standard deviation when evaluated at the average of the sample is only 0.01. 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 inputs to affected industries (columns 1 and 2).

In Table 8, we estimate a version of Eq. (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
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 1% winsorized at each tail. 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 100,000 s. Deaths/pop is the number of reported COVID-19 deaths in the state divided by the state population in 100,000 s. Distancing is the share of industry employment affected by social distancing from Kóren et al., 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. Cases/Pop industry is the weighted average of Cases/pop, weighted across states by the sector’s contribution to real GDP in the state. All (continuous) explanatory variables are standardized. 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.

| (1) Industry exposures | (2) Industry exposures | (3) Industry exposures | (4) Industry exposures | (5) Industry exposures | (6) Industry exposures |
|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| Book/Market            | -0.0705***             | -0.0705***             | -0.0706***             | -0.0695***             | -0.0703***             | -0.0714***             |
| (0.0197)               | (0.0197)               | (0.0197)               | (0.0196)               | (0.0196)               | (0.0196)               |
| Size                   | -0.0659***             | -0.0660***             | -0.0661***             | -0.0681***             | -0.0658***             | -0.0665***             |
| (0.0146)               | (0.0147)               | (0.0147)               | (0.0147)               | (0.0146)               | (0.0145)               |
| Cash                   | 0.0680***              | 0.0675***              | 0.0684***              | 0.0645***              | 0.0672***              | 0.0720**               |
| (0.00782)              | (0.00802)              | (0.00789)              | (0.00810)              | (0.00771)              | (0.00872)              |
| Cases/Pop              | 0.00709                | 0.00728                | 0.00749                | 0.00842                | 0.00675                | 0.00381                |
| (0.00802)              | (0.00798)              | (0.00784)              | (0.00803)              | (0.00804)              | (0.00837)              |
| Distancing             | -0.0234***             | -0.0242***             | -0.0225**              | -0.0190**              | -0.0250***             | -0.0315***             |
| (0.00885)              | (0.01087)              | (0.00882)              | (0.00883)              | (0.00865)              | (0.00961)              |
| Total-sold             | -0.00402               | -0.0067***             | -0.0267***             | -0.00602               | -0.00602               |
| (0.00780)              | (0.00804)              | (0.00664)              | (0.00677)              | (0.0267)***            |
| Total-intermediate     | 0.00519                | -0.0267***             | -0.0602                | (0.00677)              | 0.0267***              |
| (0.00804)              | (0.00677)              | (0.00664)              | (0.00677)              | (0.0157)               |
| Affected-sold          | -0.253***              | -0.253***              | -0.252***              | -0.252***              | -0.253***              | -0.252***              |
| (0.0125)               | (0.0125)               | (0.0126)               | (0.0126)               | (0.0122)               | (0.0124)               | (0.0120)               |
| Observations           | 3226                   | 3226                   | 3226                   | 3226                   | 3226                   | 3226                   |
| R-squared              | 0.087                  | 0.088                  | 0.088                  | 0.090                  | 0.088                  | 0.090                  |

position than smaller firms to sell or acquire goods in oligopolistic markets (e.g., Lustgarten, 1975; Stigler, 1964). 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 et al., 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, the marginal effect of a one standard deviation increase in the cash ratio when Distancing increases by one standard deviation when evaluated at the sample mean is 2.3%. 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, the marginal effect of a one standard deviation increase in firm size when Distancing increases by one standard deviation when evaluated at the sample mean is 2.8%. 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 disproportionally affected.

Moreover, we find that the previously identified adverse 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 the marginal effect of a one standard deviation increase in firm size when Affected-sold increases by one standard deviation when evaluated at the sample mean is 1.7%. 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 economic 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.

To account for changes in aggregate conditions in benchmark returns, we next control for total returns in benchmark portfolios based on deciles of the book-to-market and size variables. We do this by including fixed effects based on book-to-market and size deciles. This is tantamount to allowing for a non-linear relationship in the impact of book-to-market and size on changes in firm value. The results are presented in Table 10. Our main results are not affected.

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 Koren et al., 2020’s measure of the share of an industry’s employment affected by social distancing as measure of 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 11. We find that the results for non-essential industries are generally weaker when compared to social distancing. While we continue to find that firms that depend on the sale of products and services to affected sectors underperform otherwise identical firms when measuring affected industries using the non-essential classification (column 2), 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. Indeed, when we account simultaneously for the non-essential and social distancing variables (column 4), we find that our main results are driven by social distancing. The non-essential variables lose significance. We continue to find that firms operating in social distancing sectors and firms that depend on the sale of products and services to sectors affected by social distancing underperform otherwise identical firms. In Column 5, we test whether the effect of social distancing policies is smaller in essential sectors. We do not find any support for this.

In Table 12, we consider the possibility that social distancing and lockdown policies that declare sectors non-essential may interact and reinforce each other to influence firm stock prices. To this end, we re-estimate various specifications of Tables 6 and 8 by replacing our baseline distancing variables – Distancing, Affected-sold, and Affected-intermediate – with variables that capture the combined impact of Non-essential and Social distancing. Specifically, we include Nonessential/distancing, which indicates whether the industry is designated by CISA as non-essential and/or the industry is strongly affected by social distancing; Affected-sold (nonessential/distancing), which is the fraction of total production sold to industries affected by social distancing underperform otherwise identical firms. In Column 5, we test whether the effect of social distancing policies is smaller in essential sectors. We do not find any support for this.

In Table 12, we consider the possibility that social distancing and lockdown policies that declare sectors non-essential may interact and reinforce each other to influence firm stock prices. To this end, we re-estimate various specifications of Tables 6 and 8 by replacing our baseline distancing variables – Distancing, Affected-sold, and Affected-intermediate – with variables that capture the combined impact of Non-essential and Social distancing. Specifically, we include Nonessential/distancing, which indicates whether the industry is designated by CISA as non-essential and/or the industry is strongly affected by social distancing; Affected-sold (nonessential/distancing), which is the fraction of total production sold to industries affected by social distancing underperform otherwise identical firms. In Column 5, we test whether the effect of social distancing policies is smaller in essential sectors. We do not find any support for this.

|                  | (1) Industry exposures and firm characteristics | (2) Industry exposures and firm characteristics | (3) Industry exposures and firm characteristics |
|------------------|-----------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| Book/Market      | -0.0535*** (0.0190)                          | -0.0578*** (0.0201)                          | -0.0578*** (0.0200)                          |
| Size             | -0.0758*** (0.0135)                          | -0.0817*** (0.0147)                          | -0.0811*** (0.0156)                          |
| Cash             | 0.0139 (0.0138)                              | 0.00441 (0.0140)                             | 0.00426 (0.0147)                             |
| Book/market × Distancing | 0.0229* (0.0122)                            |                                               |                                               |
| Size × Distancing | 0.0282*** (0.00980)                         |                                               |                                               |
| Cash × Distancing | 0.0230** (0.0106)                           |                                               |                                               |
| Book/market × Affected-sold | 0.00562 (0.00790)                         |                                               |                                               |
| Size × Affected-sold | 0.0171** (0.00784)                        |                                               |                                               |
| Cash × Affected-sold | 0.00731 (0.0115)                           |                                               |                                               |
| Book/market × Affected-intermediate |                                               |                                               | 0.0110 (0.0120)                              |
| Size × Affected-intermediate |                                               |                                               | 0.00218 (0.0114)                             |
| Cash × Affected-intermediate |                                               |                                               | 0.00676 (0.0122)                             |
| 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 1% winsorized at each tail. 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 100,000 s. Distancing is the share of industry employment affected by social distancing from Kőre et al., 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. All (continuous) explanatory variables are standardized. 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.

|          | (1)          | (2)          | (3)          | (4)          | (5)          |
|----------|--------------|--------------|--------------|--------------|--------------|
| Book/Market | −0.0844**   | −0.0830**    | −0.0844**    | −0.0626*     | −0.0622*     |
| Size      | −0.105***    | −0.108***    | −0.105***    | −0.123****   | −0.121****   |
| Cash      | 0.113***     | 0.108***     | 0.113***     | 0.0252       | 0.0225       |
| Cases/pop | 0.00232      | 0.00418      | 0.00237      |              |              |
| Distancing| −0.0480***   | −0.0408***   | −0.0479***   |              |              |
| Affected-sold | −0.0372***  |              |              |              |              |
| Affected-intermediate |              |              |              | 0.000819     | (0.00979)    |
| Book/Market × Affected-sold |              |              |              | 0.00866      | (0.0130)     |
| Size × Affected-sold |              |              |              | 0.0397***    | (0.0136)     |
| Cash × Affected-sold |              |              |              | 0.0195       | (0.0198)     |
| Book/Market × Affected-intermediate |              |              |              | 0.0242       | (0.0226)     |
| Size × Affected-intermediate |              |              |              | 0.0145       | (0.0154)     |
| Cash × Affected-intermediate |              |              |              | −0.00115     | (0.0211)     |
| Constant   | −0.113***    | −0.113***    | −0.113***    |              |              |
| 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: Stock returns of book-to-market and size portfolios. The dependent variable is the firm’s total stock return over the first three months of 2020. All regressions include fixed effects based on book-to-market and size deciles (not reported). Book/market is the book-to-market value of the firm’s stock. Size is the logarithm of total assets (in millions of US dollars). Stock returns and book-to-market values are 1% winsorized at each tail. 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 100,000 s. Distancing is the share of industry employment affected by social distancing from Kőre et al., 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 (continuous) explanatory variables are standardized. 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.

|          | (1)          | (2)          | (3)          |
|----------|--------------|--------------|--------------|
| Cash     | 0.0627***    | 0.0599***    | 0.0613***    |
| Cases/pop| 0.00379      | 0.00486      | 0.00325      |
| Distancing| −0.0114     | −0.00742     | −0.0123      |
| Affected-sold | −0.0226***  |              |              |
| Affected-intermediate |              |              | −0.00898     |
| Constant  | 0.178**      | 0.177**      | 0.178**      |
| State fixed effects | No          | No           | No           |
| Industry fixed effects | No          | No           | No           |
| Observations | 3,226       | 3,226        | 3,226        |
| R-squared  | 0.086        | 0.127        | 0.125        |
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 1% winsorized at each tail. 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 100,000 s. 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. Distancing is the share of industry employment affected by social distancing from Kóren et al., 2020. Affected-sold is the fraction of total production sold to industries affected by social distancing. All (continuous) explanatory variables are standardized. 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.

|                          | (1)       | (2)       | (3)       | (4)       | (5)       |
|--------------------------|-----------|-----------|-----------|-----------|-----------|
| Book/market              | -0.0745***| -0.0746***| -0.0745***| -0.0699***| -0.0707***|
|                          | (0.0194)  | (0.0194)  | (0.0194)  | (0.0196)  | (0.0196)  |
| Size                     | -0.0653***| -0.0658***| -0.0654***| -0.0677***| -0.0653***|
|                          | (0.0146)  | (0.0146)  | (0.0145)  | (0.0147)  | (0.0146)  |
| Cash                     | 0.0785*** | 0.0766*** | 0.0789*** | 0.0644*** | 0.0679*** |
|                          | (0.00762) | (0.00781) | (0.00777) | (0.00815) | (0.00770) |
| Cases/Pop                | 0.00264   | 0.00271   | 0.00259   | 0.00853   | 0.00763   |
|                          | (0.00952) | (0.00972) | (0.00959) | (0.00786) | (0.00792) |
| Nonessential             | -0.00683  | -0.00144  | -0.00891  | -0.00831  | 0.00743   |
|                          | (0.0258)  | (0.0253)  | (0.0246)  | (0.0261)  | (0.0278)  |
| Affected-sold (nonessential) | -0.0186***| -0.00506  |           |           |           |
|                          | (0.00492) | (0.00700) |           |           |           |
| Affected-intermediate (nonessential) | 0.00351   |           |           |           |           |
|                          | (0.00799) |           |           |           |           |
| Distancing               |           | -0.0188** | -0.0196** |           |           |
|                          |           | (0.00817) | (0.00896) |           |           |
| Affected-sold            |           | -0.0239** |           |           |           |
|                          |           | (0.00957) |           |           |           |
| Nonessential × Distancing|           | -0.0371   |           | -0.0371   |           |
|                          |           | (0.0281)  |           | (0.0281)  |           |
| Constant                 | -0.254*** | -0.255*** | -0.254*** | -0.251*** | -0.252*** |
|                          | (0.0145)  | (0.0145)  | (0.0142)  | (0.0133)  | (0.0140)  |
| Observations             | 3274      | 3274      | 3274      | 3226      | 3226      |
| R-squared                | 0.087     | 0.088     | 0.087     | 0.090     | 0.088     |

Robustness check: Nonessential and/or social distancing 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 1% winsorized at each tail. Size is the logarithm of total assets (in millions of US dollars). Cash is the ratio of cash (equivalents) to total assets. Cases/pop is the number of reported COVID-19 cases in the state divided by the state population in 100,000 s. Non-essential/distancing equals one if CISA considers the industry to be nonessential and/or the industry is strongly affected by social distancing (i.e., the social distancing affected share is above its median), and zero otherwise. Affected-sold (nonessential/distancing) is the fraction of total output from intermediate products of nonessential and/or social distancing industries. Affected-intermediate (nonessential/distancing) is the fraction of total output from intermediate products of nonessential and/or social distancing industries. All (continuous) explanatory variables are standardized. Standard errors are adjusted for clustering at state-sector level and are reported between brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                          | (1)       | (2)       | (3)       | (4)       | (5)       |
|--------------------------|-----------|-----------|-----------|-----------|-----------|
| Book/Market              | -0.0737***| -0.0741***| -0.0722***| -0.0585***| -0.0566***|
|                          | (0.0195)  | (0.0195)  | (0.0253)  | (0.0203)  | (0.0200)  |
| Size                     | -0.0669***| -0.0654***| -0.105***  | -0.0820***| -0.0812***|
|                          | (0.0147)  | (0.0146)  | (0.0187)  | (0.0149)  | (0.0150)  |
| Cash                     | 0.0725*** | 0.0754*** | -0.00853  | 0.00580   | 0.00339   |
|                          | (0.00934) | (0.00934) | (0.0168)  | (0.0139)  | (0.0144)  |
| Cases/pop                | 0.00291   | 0.00220   |           |           |           |
|                          | (0.00940) | (0.00956) |           |           |           |
| Nonessential/distancing | -0.0111   | -0.0171   |           |           |           |
|                          | (0.0219)  | (0.0222)  |           |           |           |
| Affected-sold (nonessential/distancing) | -0.0244***| -0.00248  |           |           |           |
|                          | (0.00588) | (0.00678) |           |           |           |
| Book/market × Nonessential/distancing | 0.0436   |           |           |           |           |
|                          | (0.0399)  |           |           |           |           |
| Size × Nonessential/distancing | 0.0607** |           |           |           |           |
|                          | (0.0248)  |           |           |           |           |
| Cash × Nonessential/distancing | 0.0517*  |           |           |           |           |
|                          | (0.0272)  |           |           |           |           |
| Book/market × Affected-sold (nonessential/distancing) | 0.00309   |           |           |           |           |
|                          | (0.00575) |           |           |           |           |
| Size × Affected-sold     | 0.152**   |           |           |           |           |

(continued on next page)
two measures capture different dimensions of the impact of lockdown policies. Table 13 shows the results when replacing the social distancing variable with the working from home variable (column 1). We also include variables capturing the role of input–output linkages based on this working from home index (columns 2 and 3). Specifically, we include Affected-sold (working from home), which is the fraction of total production sold to industries affected by working from home, and Affected-intermediate (working from home), which is the fraction of total output consisting of intermediate products from industries affected by working from home. In Column 4, we include the Social distancing variables alongside the Working from home variables. The working from home variables do not enter significantly, while the coefficients on the social distancing are virtually unaltered when compared to our baseline results.

Table 12 (continued)

| (1)          | (2)          | (3)          | (4)          | (5)          |
|--------------|--------------|--------------|--------------|--------------|
| (nonessential/distancing) | (nonessential/distancing) | (nonessential/distancing) | (nonessential/distancing) | (nonessential/distancing) |
| Book/market × Affected-intermediate | 0.0151       | 0.0144       | 0.00878      | 0.00812      |
| Size × Affected-intermediate | 0.0165*      | (0.0048)     | (0.0148)     | (0.0147)     |
| Cash × Affected-intermediate | 0.00606      | (0.00844)    | (0.0120)     | (0.0140)     |
| Affected-sold (working from home) | 0.0198       | (0.00844)    | (0.0120)     | (0.0140)     |
| Affected-intermediate (working from home) | 0.0388       | (0.00754)    | (0.0120)     | (0.0140)     |

Table 13

Robustness check: Working from home 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 100,000 s. Working from home is the share of the sector’s employment that can be done from home from Dingel and Neiman (2020). Affected-sold (working from home) is the fraction of total production sold to industries affected by working from home. Affected-intermediate (working from home) is the fraction of total output consisting of intermediate products from industries affected by working from home. Distancing is the share of industry employment affected by social distancing from Kóren et al., 2020. Affected-sold is the fraction of total production sold to industries affected by social distancing. ICT sector equals one if the firm operates in the Information and Communications Technologies sector, and zero otherwise. All (continuous) explanatory variables are standardized. 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.

| (1)          | (2)          | (3)          | (4)          | (5)          |
|--------------|--------------|--------------|--------------|--------------|
| Book/market  | −0.0749***   | −0.0752***   | −0.0748***   | −0.0702***   | −0.0683***   |
|              | (0.0197)     | (0.0197)     | (0.0197)     | (0.0197)     | (0.0195)     |
| Size         | −0.0653***   | −0.0659***   | −0.0653***   | −0.0684***   | −0.0679***   |
|              | (0.0148)     | (0.0149)     | (0.0148)     | (0.0147)     | (0.0147)     |
| Cash         | 0.0084***    | 0.0086***    | 0.0086***    | 0.0081***    | 0.0065***    |
|              | (0.00877)    | (0.00881)    | (0.00889)    | (0.00883)    | (0.00831)    |
| Cases/Pop    | 0.00177      | 0.00194      | 0.00179      | 0.00580      | 0.00887      |
|              | (0.00958)    | (0.00970)    | (0.00956)    | (0.00799)    | (0.00810)    |
| Working from home | 0.00654     | 0.0161       | 0.00859      | 0.0167       | 0.0198       |
|              | (0.0120)     | (0.0140)     | (0.0135)     | (0.0119)     | (0.0147)     |
| Affected-sold (working from home) | −0.0161*      |          |          |          |          |
|              | (0.00844)    | (0.00844)    | (0.0120)     | (0.0140)     | (0.0147)     |
| Affected-intermediate (working from home) | −0.0388       |          |          |          |          |
|              | (0.00754)    | (0.00754)    | (0.0120)     | (0.0140)     | (0.0147)     |
| Distancing   | −0.0173**    | −0.0184**    |          |          |          |
|              | (0.00856)    | (0.00910)    | (0.0130)    | (0.00861)    | (0.0130)    |
| Affected-sold | −0.0486***   | −0.0305***   |          |          |          |
|              | (0.0130)     | (0.0061)     | (0.0130)    | (0.0061)     | (0.0130)    |
| ICT sector   | 0.0256**     | (0.0359)     | (0.0359)    | (0.0377)     | (0.0391)    |
| Observations | 3274         | 3274         | 3274        | 3226         | 3226        |
| R-squared    | 0.087        | 0.088        | 0.087       | 0.092        | 0.093       |

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An alternative approach to accounting for the importance of working from home effects is to explore whether our main results depend on the sensitivity of the firm’s sector to work-from-home policies. For instance, given the forward-looking nature of stock market prices, firms that operate in technology sectors may have experienced increases in stock market returns, as work-from-home policies required the use of technological products such as software and IT equipment. To test for such differential effects, in Column 5 we include a dummy variable indicating whether the firm operates in the IT sector, as well as its interactions with the Social distancing variables. We define the IT sector as the combination of the following four-digit NAICS codes: Computer and Peripheral Equipment Manufacturing (3341), Software publishers, internet publishing and broadcasting (5112, 5161), Telecommunications (5171–5174, 5179), Internet service providers, web search portals, data processing, hosting, and related services (5181, 5182), and Computer Systems Design and Related Services (5415). As expected, we find that the firms in the IT sector outperform other firms and they benefit from the direct effect of social distancing. However, they are equally adversely affected by the indirect effect operating through input–output linkages, as captured by the Affected-sold variable. These results imply that even the IT sector, which overall benefited from the shock, was not immune to the adverse indirect effects of social distancing operating through input–output linkages. These results therefore lend additional support to our premise that input–output linkages play an important role in the propagation of shocks during the COVID-19 crisis.

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 2.4%, while a one standard deviation increase in Affected-sold (the indirect effect) is associated with a decline in stock returns of 2.7%. 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.

Declaration of Competing Interest

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

Appendix A

See Tables A1 and A2.
Table A1
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 et al., 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                  |
Table A2
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 date indicates the date in 2020 that the state governor announced a statewide lockdown. The date is missing for states that did not issue a statewide lockdown by mid-April 2020.

| State                  | Cases/pop | Deaths/pop | Lockdown date |
|------------------------|-----------|------------|---------------|
| Alabama                | 20.0      | 0.3        | April 4       |
| Alaska                 | 16.3      | 0.4        | March 27      |
| Arizona                | 17.7      | 0.3        | March 30      |
| Arkansas               | 17.3      | 0.3        | –             |
| California             | 18.9      | 0.4        | March 19      |
| Colorado               | 45.6      | 0.9        | March 25      |
| Connecticut            | 87.7      | 1.5        | March 20      |
| Delaware               | 32.8      | 1.0        | March 22      |
| District of Columbia   | 70.1      | 1.3        | March 30      |
| Florida                | 29.5      | 0.4        | April 1       |
| Georgia                | 37.0      | 1.0        | April 2       |
| Hawaii                 | 14.4      | 0.0        | March 23      |
| Idaho                  | 23.2      | 0.4        | March 25      |
| Illinois               | 47.3      | 0.8        | March 20      |
| Indiana                | 32.1      | 0.7        | March 23      |
| Iowa                   | 15.8      | 0.2        | –             |
| Kansas                 | 14.7      | 0.3        | March 28      |
| Kentucky               | 10.7      | 0.2        | March 25      |
| Louisiana              | 112.7     | 5.1        | March 22      |
| Maine                  | 22.5      | 0.4        | March 31      |
| Maryland               | 27.5      | 0.3        | March 30      |
| Massachusetts          | 94.6      | 2.2        | March 23      |
| Michigan               | 118.9     | 2.6        | March 23      |
| Minnesota              | 11.2      | 0.2        | March 25      |
| Mississippi            | 31.5      | 0.7        | April 1       |
| Missouri               | 21.6      | 0.2        | April 3       |
| Montana                | 17.2      | 0.4        | March 26      |
| Nebraska               | 8.9       | 0.2        | –             |
| Nevada                 | 36.1      | 0.6        | April 1       |
| New Hampshire          | 23.1      | 0.2        | March 26      |
| New Jersey             | 210.5     | 3.0        | March 21      |
| New Mexico             | 13.4      | 0.2        | March 23      |
| New York               | 389.6     | 8.0        | March 20      |
| North Carolina         | 14.3      | 0.1        | March 27      |
| North Dakota           | 16.5      | 0.4        | –             |
| Ohio                   | 18.8      | 0.5        | March 22      |
| Oklahoma               | 14.3      | 0.6        | –             |
| Oregon                 | 16.4      | 0.4        | March 23      |
| Pennsylvania           | 37.8      | 0.5        | April 1       |
| Rhode Island           | 46.2      | 0.8        | March 28      |
| South Carolina         | 21.0      | 0.4        | April 6       |
| South Dakota           | 12.2      | 0.1        | –             |
| Tennessee              | 32.8      | 0.3        | April 2       |
| Texas                  | 11.3      | 0.1        | March 31      |
| Utah                   | 27.7      | 0.2        | –             |
| Vermont                | 47.0      | 2.1        | March 24      |
| Virginia               | 14.6      | 0.3        | March 30      |
| Washington             | 90.7      | 3.4        | March 23      |
| West Virginia          | 9.0       | 0.1        | March 23      |
| Wisconsin              | 23.2      | 0.3        | March 24      |

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