Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks*

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Abstract

This paper examines whether firm-level idiosyncratic shocks propagate in production networks. We identify idiosyncratic shocks with the occurrence of natural disasters. We find that affected suppliers impose substantial output losses on their customers, especially when they produce specific inputs. These output losses translate into significant market value losses, and they spill over to other suppliers. Our point estimates are economically large, suggesting that input specificity is an important determinant of the propagation of idiosyncratic shocks in the economy.

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Introduction

The origin of business cycle fluctuations is a long-standing question in economics. Starting with Long and Plosser (1983), a number of studies have explored whether sectoral linkages may help explain the aggregation of sector-specific shocks, and have found mixed empirical evidence of the importance of such linkages. Relative to spillovers across sectors, spillovers within networks of firms have received little attention in the literature. The main reason for this is the difficulty of identifying firm-specific shocks. Whether or not firm-level idiosyncratic shocks propagate in production networks therefore remains an open question.

On the one hand, firm-level idiosyncratic shocks should be quickly absorbed in production networks. Firms plausibly organize their operations to avoid being affected by temporary disruption to their supplies. Even when they face such disruptions, they might be flexible enough to recompose their production mix, or to switch to other suppliers. The gradual decrease in trade tariffs and transportation costs, as well as the development of online business should make it even easier for firms to adjust their sourcing. On the other hand, frictions might prevent firms from quickly making adjustments in the event of supply disruptions. If firms face switching costs whenever they need to replace a disrupted supplier, idiosyncratic shocks might propagate from firm to firm, and gradually be amplified.

This paper studies whether firm-level shocks propagate, or whether they are absorbed in production networks. To identify firm-level idiosyncratic shocks, we consider major natural disasters in the past thirty years in the U.S.[1] These events have large short-term effects on the sales growth of affected firms. We trace the propagation of these shocks in production networks using supplier-customer links reported by publicly listed U.S. firms. If disrupted intermediate inputs can be easily substituted, we should not expect input shocks to propagate significantly.

[1] Natural disasters have already been used in prior work to instrument for school displacement (Imberman et al., 2012), positive local demand shocks (Bernile et al., 2013), temporary shocks to local labor markets (Belasen and Polachek, 2008), changes in uncertainty (Baker and Bloom, 2013), and changes in risk perception (Dessaint and Matray, 2013).

Yet, we find that suppliers hit by a natural disaster impose significant output losses on their customers. When one of their suppliers is hit by a major natural disaster, firms experience an average drop of 2 percentage points in sales growth following the event. Given that suppliers represent a small share of firms' total intermediate inputs in our sample, these estimates are strikingly large. We show that these estimates are robust to controlling for the location of firms' establishments. In addition, we do not find any evidence of propagation from suppliers to customers when they are not in an active relationship, which suggests that these estimates are not driven by common demand shocks triggered by natural disasters.

We investigate whether the drop in firms' sales caused by supply disruptions translates into value losses. If input disruptions simply cause a delay in sales, they would have little effect on firms' cash flows, and ultimately on firm value. However, we do not observe any sort of overshooting in sales on average following disasters, suggesting that these sales are lost indeed. We also conduct event studies and estimate firms' cumulative abnormal returns around disaster events affecting one of their suppliers. We find that input disruptions cause a 1% drop in firms' equity value. Again, the effect is almost twice as large when the disrupted supplier is a *specific* supplier, i.e., a supplier producing differentiated goods, generating high R&D expenses, or holding patents.

We then show that input specificity is a key driver of the propagation of firm-level shocks. To do so, we construct three measures of suppliers' specificity. The first one borrows from the Rauch (1999) classification of goods traded on international markets. Second, we use suppliers' R&D expenses to capture the importance of relationship-specific investments. Finally, we use the number of patents issued by suppliers to capture restrictions on alternative sources of substitutable inputs. Each of these measures is strongly correlated with the empirical duration of supplier-customer relationships, suggesting that they capture variations in the cost for customers to switch suppliers.[2] We find that the propagation of input shocks varies strongly with our measures of specificity. Firms' sales growth and stock prices signif-

[2]We also check that the intensity of shocks affecting suppliers or the relative size of the supplier do not systematically vary with our measures of input specificity, in a manner that could drive the results.

icantly drop only when a major disaster hits one of their *specific* suppliers.

We also ask whether the shock originating from one supplier propagates horizontally to other suppliers of the same firm, which were not *directly* affected by the natural disaster. Even though firms reduce output when one of their suppliers is hit, they could very well keep buying from their other suppliers, and even start buying more. Even if the customer reduces purchases from all its suppliers following the disruption of one of its inputs, other suppliers might be able to find alternative buyers for their production. Instead, we find large negative spillovers of the initial shock to other suppliers. The effect is only observed when the disaster hits a specific supplier. We show that our estimates are robust to controlling for the location of suppliers' establishments. Moreover, we do not find evidence of horizontal propagation when the economic link between firms is inactive, which confirms that our estimates are not driven by common demand shocks.

Finally, we discuss the economic significance of our estimates. We first ask whether the drop in firms' sales growth is compensated by an increase in the sales of their competitors, so that the aggregate output of their sector remains unaffected. To do so, we combine data from the U.S. Industrial Production Index and the BEA input-output matrix. We find that shocks affecting *specific* upstream sectors have a negative effect on downstream sectors' real output growth. This confirms that, on average, specific input disruptions translate into sector-wide output losses. In addition, we compute the aggregate dollar value of sales lost for suppliers and customers in our sample. We find that \$1 dollar of lost sales at the supplier level leads to \$3.6 of lost sales at the customer level, which indicates that propagation in production networks is substantial.

Overall, our findings highlight that the specificity of intermediate inputs allows idiosyncratic shocks to propagate in production networks. They echo numerous press reports indicating that natural disasters have important disruptive effects that propagate along the supply chain.[3] They also highlight the presence of strong interdependencies in production

[3]See for instance: "Hurricane Isaac: Lessons For The Global Supply Chain" (Forbes, 8/31/2012), "A Storm-Battered Supply Chain Threatens Holiday Shopping" (New York Times, 4/11/2012).

networks, which are highly relevant in order to assess the implications of corporate bailouts.[4]

This paper contributes to several strands of the literature. It relates to a growing body of work assessing whether significant aggregate fluctuations may originate from microeconomic shocks. This view has long been discarded on the basis that these shocks would average out, and thus would have negligible aggregate effects (Lucas, 1977). Two streams of papers challenge this intuition: the first is based on the idea that large firms contribute disproportionately to total output (Gabaix, 2011; Carvalho and Gabaix, 2013); the second stream posits that shocks are transmitted in the economy through industry linkages (Long and Plosser, 1987; Jovanovic, 1987; Durlauf, 1993; Bak et al., 1993; Horvath, 1998, 2000; Conley and Dupor, 2003; Di Giovanni and Levchenko, 2010; Carvalho, 2010; Caselli et al., 2011; Acemoglu et al., 2012; Bigio and LaO, 2013). However, the empirical evidence on the importance of sector linkages for the aggregation of sector-specific shocks is mixed and depends on the level of aggregation (Horvath, 2000), the way linkages are modeled (Foerster et al., 2011), and the specification of the production function (Jones, 2011; Atalay, 2013). While earlier work has focused on the linkages across sectors,[5] we carefully estimate linkages within networks of firms.[6] In contemporaneous work, Todo et al. (2014) and Carvalho et al. (2014) study the supply-chain effects of the Japanese earthquake of 2011. Our setting, which encompasses multiple natural disasters over a period of thirty years allows us to disentangle input disruptions from common demand shocks, and to cleanly identify the importance of input specificity for the propagation and amplification of idiosyncratic shocks. We also add to this literature by documenting that in addition to propagating to downstream firms, idiosyncratic shocks also propagate horizontally into supplier networks.

Furthermore, we build on earlier work that considers the importance of switching costs

[4]In its testimony to the Senate Committee on Banking, Housing, and Urban Affairs on December 4, 2008, Ford CEO Alan Mulally said: "The collapse of one or both of our domestic competitors would threaten Ford because we have 80 percent overlap in supplier networks and nearly 25 percent of Ford's top dealers also own GM and Chrysler franchises."

[5]Di Giovanni et al. (2014) is a recent exception.

[6]While this paper takes the network structure as given, Chaney (2011), Oberfield (2013), and Carvalho and Voigtländer (2014) among others explicitly model the formation of business networks.

for the propagation of firm-level shocks. A number of studies have analyzed the role of switching costs in banking relationships for the diffusion of financial shocks (Slovin et al., 1993; Hubbard et al., 2002; Khwaja and Mian, 2008; Fernando et al., 2012). Amiti and Weinstein (2013) and Chodorow-Reich (2014) find that such frictions can explain a large share of the aggregate drop in investment and employment in the recent financial crisis. We show that switching costs between trade partners are substantial, and can explain the propagation of shocks in networks of non-financial firms. The existence of costs of searching for suppliers is a key parameter in recent studies of firms' sourcing decisions (Antras et al., 2014; Bernard et al., 2014). Our findings suggest that these costs can be large in the short-run.

We also add to a growing body of work in financial economics that studies how firms are affected by their environment, and in particular by their customers and suppliers. Recent studies have found evidence of comovement in stock returns within production networks (Cohen and Frazzini, 2008; Hertzel et al., 2008; Menzly and Ozbas, 2010; Ahern, 2012; Boone and Ivanov, 2012; Kelly et al., 2013). Our results, which emphasize the importance of input complementarity and switching costs, provide a foundation for this comovement. In addition, our results also relate to prior studies of the implications of product market relationships for firms' corporate policies (Titman, 1984; Titman and Wessels, 1988; MacKay and Phillips, 2005; Kale and Shahrur, 2007; Campello and Fluck, 2007; Banerjee et al., 2008; Chu, 2012; Moon and Phillips, 2014; Ahern and Harford, 2014). A key result of this literature is that firms whose suppliers need to make relationship-specific investments hold less leverage to avoid imposing high liquidation costs on them. Our results suggest that an alternative reason why firms linked to specific suppliers hold less leverage is to avoid the risk of financial distress brought about by input disruptions.

The remainder of the paper is organized as follows. In Section 1, we use a simple framework to derive the conditions under which input shocks propagate in production networks. Section 2 presents our empirical strategy. Section 3 presents the data; Section 4 describes the results, and Section 5 concludes.

1. Theoretical framework

Should firms be affected by disruptions of their supplies of intermediate inputs? In Appendix A.1, we present a simple framework that delivers predictions of the magnitude of the pass-through of input shocks to firms' output. We start with a standard constant-returns-to-scale production function. The quantity of capital is fixed in the short-run, and the firm chooses the quantities of labor and intermediate inputs in order to maximize profits. We express the response of a representative firm's output to a small deviation in the availability of one of its intermediate inputs. We obtain the following insights.

First, the effect on output of a drop in the availability of an intermediate input increases with the degree of complementarity between intermediate inputs. When intermediate inputs are perfect substitutes, the firm's production is unaffected by a disruption in the supply of one input. Firms offset the drop in the disrupted input by using simply more of the other intermediate inputs. By contrast, when intermediate inputs are perfect complements,[7] the pass-through can be relatively high, irrespective of the cost share of the disrupted input in production.

The second insight relates to the reaction of other intermediate inputs to the disruption in the supply of one input. The pass-through rate of a given input shock to other intermediate inputs can be either positive or negative. If intermediate inputs are strong substitutes, the pass-through rate is negative, i.e., the disruption of an intermediate input leads to an increase in the use of other inputs. In sharp contrast, if intermediate inputs are strong complements, the pass-through rate is positive, and can even be larger than the effect on total production. The intuition for this result is that, in response to a shock to a given input, the share of intermediate inputs in production will drop, as the substitution towards labor outweighs the substitution across intermediate inputs.

[7] This limit case is the Leontief (1936) production function.

This simple theoretical framework is helpful to think about the empirical relationships between the output growth of a supplier caused by a natural disaster, of the firm using this input, and of the firm's other suppliers of intermediate inputs.[8] The key prediction for our analysis is the following: when the constrained input cost share is small – as it is on average in our sample[9] – the size of the pass-through is small unless intermediate inputs are strong complements.

Empirically, we would expect to find an effect only when the firm faces relatively large costs of searching for, and switching to alternative suppliers of the same input. Otherwise, following the disruption of the supplier of a given intermediate input, the firm would turn to other providers of the same input, and maintain its first-best level of output. Hence, the size of the pass-through rate should increase with the specificity of the input provided by the disrupted supplier.

Similarly, we would expect to find spillovers of the initial shock to other suppliers only if they cannot easily switch to alternative customers. Moreover, if the customer can easily replace the disrupted supplier, then its demand for other intermediate inputs should not change, so that other suppliers will remain unaffected. Therefore, the magnitude of spillovers should increase with the specificity of the input provided by the disrupted supplier.

2. Identification strategy

The main source of identification in this paper is the occurrence of major natural disasters. We identify disruptions to suppliers' output in a given quarter with the event that the county

[8] One of the limitations of this exercise is that we have assumed that input prices are fixed. Assuming that the price of an input rises when that input is disrupted would generate an additional amplification mechanism, whereby the firm might willingly reduce its use of the disrupted input if its price rises too much. Note however that prior literature has provided consistent evidence on the stickiness of prices in the short run. Very relevant for our study, Cavallo et al. (2014) find that supermarket prices remained stable for several months following the 2010 earthquake in Chile and the 2011 earthquake in Japan, even for goods that were experiencing severe stockouts. Using questionnaire responses from respectively U.S., U.K., and Swedish firms, Blinder et al. (1998), Hall et al. (2000) and Apel et al. (2005) highlight the importance of both implicit and explicit contracts in explaining the rigidity of prices between suppliers and their customers.

[9] The average suppliers' input share in firms' cost of goods sold in our sample is 2.2%, see Table 2.

where their headquarters is located is hit by a natural disaster. Of course, firms' plants and establishments are not always located in the same county as their headquarters. However, this measurement error is likely to bias the estimates against finding any effect of natural disasters on firms' output. In addition, using establishment-level data from Infogroup,[10] we find that in our sample of suppliers, the average (median) firm has 57% (62%) of its employees located at its headquarters (see Table 2).

There are many different but unobservable reasons why disasters might affect firms' output. It might be that they trigger power outages disrupting production.[11] Alternatively, it might be that assets including buildings, machines, or inventories are damaged. Finally, firms' workforce or management might be prevented from reaching the workplace. Although we have no way to pin down the exact channel through which disasters disrupt production, we confirm in Section 4 that such disasters have a temporary and significant negative effect on these suppliers' sales growth.[12]

The main focus of the paper is not the disruption to the supplying firm itself, but rather the impact on the firm's customers, as well as on the customers' other suppliers. Our identification strategy closely approximates the following example. Assume that firm S1 is a supplier to firm C, who also purchases input from firm S2. Suppose, however, that S1 and S2 do not have any economic links other than their relationship with C. We first analyze the response of C when S1 is hit by a natural disaster. We then focus on the response of S2. In each case, we contrast these effects with characteristics that capture the cost of replacing S1 with another provider of the same input.

To capture supplier-customer links, we rely on the obligation that publicly listed firms have in the U.S. to report any customer accounting for more than 10% of their sales.[13] We consider that S1 is a supplier to C in all years ranging from the first to the last year when

[10] We describe the data in more detail in Section 3.

[11] Hines et al. (2008) find that 44% of major power outages in the U.S. are weather-related (i.e., caused by tornado, hurricane/tropical storm, ice storm, lightning, wind/rain, or other cold weather).

[12] Following standard event methodology, we also find that firms experience a significant stock price decline following the date of a major disaster hitting the county location of their headquarters.

[13] We describe the data in more detail in Section 3.

S1 reports C as one of its customers. We then estimate the effect of the shock to S1 on C's sales growth in a difference-in-differences framework at the firm level, where the treatment amounts to having at least one supplier hit by a natural disaster.

We run the following OLS regression at the firm-quarter level in our sample of customers,[14]

$$\Delta Sales_{i,t,t+4} = \alpha_0 + \alpha_1.HitsSupplier_{i,t} + \alpha_2.HitsFirm_{i,t} + \eta_i + \pi_t + \epsilon_{i,t}, \quad (1)$$

where $\Delta Sales_{i,t,t+4}$ is the sales growth between the current quarter and the same quarter in the following year. $HitsSupplier_{i,t}$ is a dummy taking the value of one if at least one of the firm's suppliers is located in a county hit by a natural disaster. $HitsFirm_{i,t}$ is a dummy equal to one if the firm is directly hit by a natural disaster. η_i and π_t are year-quarter and firm fixed effects. All regressions control for fiscal-quarter fixed effects. In some specifications, we include industry×year fixed effects and state×year fixed effects. We also introduce lagged controls for size, age, and profitability interacted with year-quarter fixed effects.[15] We build these controls by interacting year-quarter dummies with terciles of firms' assets, age, and return on assets two years prior to date t. In all regressions, standard errors are clustered at the firm level to account for serial correlation of the error term within firms. The coefficient of interest is α_1, which measures the effect on the firm's sales growth of a disruption to at least one of its suppliers.

For our strategy to consistently estimate the effect of the shock to S1 on C, we need to make several identifying assumptions. First, C's sales growth would have been flat in the absence of treatment (parallel trends assumption). We will check whether we find any effect in the quarter prior to the natural disaster, and also formally test whether eventually treated and never treated firms experience diverging trends over the sample period.

Second, the natural disaster should affect C only through its disruptive effect on S1

[14]The benefit of using sales is that it is available at the quarterly level for all publicly listed U.S. firms, which is the ideal frequency to study the temporary disruptions caused by natural disasters. The drawback is that sales reflect prices and quantities. However, in Section 4, we show that similar results are obtained at the sector level using a quarterly index of industrial output.

[15]Including these controls ensures that the estimates are not driven by heterogeneous trends among large, old, or profitable firms.

(exclusion restriction). However, this assumption might be violated if C's own production facilities are affected by the disaster. We handle this problem by excluding from the sample any supplier-customer relationships where both parties' headquarters are located in the same state. In addition, we add a dummy in the regression which captures whether the headquarters county location of C is hit by a natural disaster. Finally, we use establishment-level data to control for the fact that plants of C might be directly hit by disasters affecting S1. The exclusion restriction might otherwise be violated if C's demand is affected by the disaster hitting one of its suppliers, for instance because its customer base is located close to its supplier base. If this were the case, disasters hitting the supplier's location would presumably affect the customer irrespective of whether their economic link was active or not. We address this concern by checking that the effect is only present when the economic link between S1 and C is active.

One might also worry that firms endogenously select their location – and the location of their suppliers – by taking into account the fact that natural disasters will disrupt their production. This is not a threat to the identification strategy: if anything, this should bias the results against finding any propagation effects. However, it might affect the external validity of these estimates, a point that we discuss in Section 4.5. A related concern is that firms might insure against the consequences of natural disasters. Again, this would bias the results against finding any propagation effects. Nonetheless, prior studies as well as anecdotal evidence suggest that firms do not systematically insure against these risks.[16]

We then contrast the effects with the extent to which the customer can switch to other suppliers of a given input. We hypothesize that suppliers are more likely to produce specific inputs if they operate in industries producing differentiated goods as defined by Giannetti

[16] Froot (2001) and Garmaise and Moskowitz (2009) show that there are inefficiencies in the catastrophe insurance market, which lead to partial coverage of this risk at the firm level. The choice of *not* insuring against catastrophe event risk is explicitly mentioned in some annual reports, see e.g. Walmart 2013 Annual Report: *"In light of the substantial premiums payable for insurance coverage for losses caused by certain natural disasters, such as hurricanes, cyclones, typhoons, tropical storms, earthquakes, floods and tsunamis in the current insurance market, as well as the limitations on available coverage for such losses, we have chosen to be primarily self-insured with respect to such losses. [...] Significant losses caused by such events could materially adversely affect our financial performance."*

et al. (2011), if they have a high level of R&D, or if they hold patents. Using these three different proxies to measure the specificity of any given supplier, we augment Equation (1) as follows:

$$\Delta Sales_{i,t,t+4} = \beta_0 + \beta_1.HitsSupplier.NS_{i,t} + \beta_2.HitsSupplier.S_{i,t} + \beta_3.HitsFirm_{i,t} + \eta_i + \pi_t + \epsilon_{i,t} \quad (2)$$

where $HitsSupplier.NS_{i,t}$ is a dummy taking the value of one if at least one *non-specific* supplier of the firm is hit by a natural disaster. $HitsSupplier.S_{i,t}$ is another dummy taking the value of one if at least one *specific* supplier of the firm is hit by a natural disaster. The coefficients of interest are β_1 and β_2, which measure the effect on the firm's sales growth of a disruption to its non-specific and specific suppliers.

Finally, we study the effect of the initial shock on S1 on any other supplier S2 of C. To do so, we run the following OLS regression in our sample of suppliers, at the firm-quarter level,

$$\Delta Sales_{i,t,t+4} = \gamma_0 + \gamma_1.HitsCustSup_{i,t} + \gamma_2.HitsCust_{i,t} + \gamma_3.HitsFirm_{i,t} + \eta_i + \pi_t + \epsilon_{i,t} \quad (3)$$

where $HitsCustSup_{i,t}$ is a dummy taking the value of one if at least one other supplier of the firm's customer(s) is hit by a natural disaster. $HitsCust_{i,t}$ is a dummy taking the value of one if (at least) one customer of the firm is hit by a natural disaster. Finally, $HitsFirm_{i,t}$ is a dummy equal to one if the firm is directly hit by a natural disaster. The coefficient of interest is γ_1, which measures the effect on the firm's sales growth of a disruption to the production function of its customer triggered by the fact that another supplier was hit by a natural disaster. [17]

[17] This test rests on the same assumptions needed to identify the effect of the natural disaster on C. In particular, it needs to be the case that the natural disaster should affect S2 only through its disruptive effect on S1, and its indirect effect on C. The exclusion restriction might be violated if S2's production facilities are affected by the disaster hitting S1. We drop from the sample any relationship where S2 is located in the same state as S1 or C. We also drop relationships where S2 is a customer or a supplier of S1. In addition, we use establishment-level data to control for the fact that plants of S2 might be directly affected by disasters. The exclusion restriction might alternatively be violated if S2's demand is affected by the disaster hitting S1, for instance because its customer base is located close to S1. If this were the case, disasters hitting S1 would presumably affect S2 irrespective of whether they were linked through their relationship with C. We address this concern by checking that disasters hitting S1 only affect S2 when the economic link between S1 and C is active, and when the economic link between S2 and C is active.

3. Data

3.1. Firm level information

Financial data and information about firm headquarters location are retrieved from Compustat North America Fundamentals Quarterly database. We restrict our sample to non-financial firms whose headquarters are located in the U.S. over the 1978-2010 period.[18] We restrict the sample to firms reporting in calendar quarters. All continuous variables are winsorized at the 1st and 99th percentiles of their distributions. We adjust our computation of the growth in sales and cost of goods sold for inflation using the GDP deflator of the Bureau of Economic Analysis.

As already mentioned, we use the county location of headquarters to identify whether a firm is hit by a natural disaster. We make an important adjustment to the (county and state) location of the headquarters of the firms in our sample. Compustat only records the last available location of the headquarters of each firm. We update the county and state of each firm in our sample using information gathered by Infogroup, which goes back as far as 1997.[19] In addition, we use employment and establishment information from Infogroup to construct controls for whether more than 10% of employees of a firm across all establishments are hit by a natural disaster.[20] Finally, we construct the 48 Fama-French industry dummies from the conversion table in the appendix of Fama and French (1997) using the firm's 4-digit SIC industry code.

We also examine below the effect of input disruptions on stock prices. For this, we obtain data on daily stock prices from the Center for Research in Security Prices (CRSP daily file). We focus on ordinary shares of stocks traded on NYSE, AMEX and NASDAQ.

[18] Customer-supplier links detailed below are available only from 1978; 2010 is the last year for which data on major natural disasters are available.

[19] This leads to a non-negligible adjustment. Between 1997 and 2010, the county location of firms' headquarters is corrected for 13% (respectively 15%) of observations in our sample of customers (respectively suppliers). For years before 1997, we update the county and state location of firms using the nearest available year in Infogroup.

[20] Infogroup makes phone calls to establishments to gather, among other data items, the number of full-time equivalent employees.

3.2. Supplier-customer links

Crucial to our analysis is the identification of relationships between suppliers and their customers. Fortunately, regulation SFAS No. 131 requires firms to report selected information about operating segments in interim financial reports issued to shareholders. In particular, firms are required to disclose certain financial information for any industry segment that comprises more than 10% of consolidated yearly sales, assets, or profits, and the identity of any customer representing more than 10% of the total reported sales.

We take advantage of this requirement to obtain information on supplier-customer links. For each firm filing with the SEC, we obtain the name of its principal customers and associated sales from the Compustat Segment files from 1978 to 2010.[21] Given that we are mainly interested in publicly listed customers for which accounting data is available, we associate each name to a Compustat identifier by hand. More specifically, we use a phonetic string matching algorithm to match each customer name with the five closest names from the set of firms filing with the SEC as well as all their subsidiaries. We then select the best match by hand by inspecting the firm and customer's names and industries. Customers with no match are excluded from the sample.

Customers in our dataset represent approximately 75% of the total sales in Compustat over the sample period, which makes us confident that the sample is representative of the U.S. economy. There are, however, limitations associated with this data. In particular, we generally do not observe suppliers whose sales to the customer are lower than 10% of their revenues.[22] Fortunately, Atalay et al. (2011) show that the truncation issue does not affect the shape of the in-degree distribution: the fraction of suppliers that we miss because of the 10% rule is similar for customers with many or few suppliers. In addition, given that our main interest lies in the reaction of customers, the fact that we are missing some of

[21]Other papers have used the customer-supplier data, including Fee and Thomas (2004), and Fee et al. (2006), who analyze respectively, the effect of mergers and corporate equity ownership on the value of suppliers.

[22]Some firms voluntarily report the names of other major customers when sales are below this threshold.

their suppliers introduces noise which is likely to bias the results against finding any sort of propagation.

3.3. Natural disasters

We obtain information on each major natural disaster hitting the U.S. territory from the SHELDUS (Spatial Hazard and Loss Database for the United States) database maintained by the University of South Carolina. For each event the database provides information on the start date, the end date, and the Federal Information Processing Standards (FIPS) code of all affected counties. We restrict the list to events classified as major disasters that occurred after 1978, which is when supplier-customer data become available. We also restrict the sample to disasters lasting less than thirty days with total estimated damages above one billion 2013 constant dollars. As evidenced in Table 1, we are left with thirty five major disasters of all kinds, including blizzards, earthquakes, floods, and hurricanes. These disasters affect a broad range of U.S. states and counties over the sample period. However, they are generally very localized and affect at most 15.7% of U.S. employment.[23] Figure 1 shows the frequency of occurrence of major natural disasters over the sample period for each U.S. county. Some counties are more frequently hit than others, especially those located along the south-east cost of U.S. mainland. In comparison, as evidenced in Figure 2, the location of suppliers in the sample spans the entire U.S. mainland, including both counties that are never and often hit by natural disasters.

3.4. Input specificity

We rely on three different proxies to measure the specificity of any given supplier. We first use the Giannetti et al. (2011) classification of 2-digit SIC codes industries (itself based on the Rauch (1999) product classification) in either differentiated goods industries, standardized

[23]Most of the events affect less than 10% of U.S. employment, which provides us with an ideal setting to cleanly identify input disruptions from general equilibrium effects. We further check that the estimates are similar for relatively small and relatively large natural disasters (see Table A.4).

goods industries or services. A supplier is thus considered as specific if it operates in an industry producing differentiated goods. We also proxy for the level of specificity with the ratio of R&D to sales, and we classify suppliers as specific if this ratio lies above the sample median in the two years prior to any given quarter. Finally, suppliers holding patents are more likely to produce inputs that cannot be easily replaced by other suppliers. Hence, in each quarter, we also sort firms based on the number of patents they issued in the previous five years and consider as specific those lying above the sample median. To do so, we retrieve patent information from Google patents assembled by Kogan et al. (2012).[24]

3.5. Summary statistics

Table 2 presents summary statistics for our sample. Panel A presents the customer sample, which consists of 60,682 firm-quarters between 1978 and 2010. There are 2,014 firms in this sample. A firm is included in the sample in each quarter between the first and last year it appears as a customer in the Compustat Segment files. On average, a firm is reported by 2 suppliers in a given year. The main variables of interest are the growth in sales and cost of goods sold over the following four quarters. The sample averages for these variables are 9.1% and 9.6%, and their medians are 3.9% and 3.7%. The probability that at least one of the suppliers of a given firm is hit by a natural disaster in any quarter is 1.9%. This compares with the probability of 1.4% that the customer is directly hit by a natural disaster.

There are on average five to seven years between the first and the last year a supplier reports a firm as a customer. Specific suppliers have longer relationships with their customers, which is consistent with the idea that it is more costly for customers to breach these relationships. The average sales of suppliers to their customers (identified with variable SALECS in the Compustat Segment files) represents 2.2% of firms' cost of goods sold. Given that wages and associated costs represent a large share of cost of goods sold, this is probably an underestimate of the importance of these suppliers in customers inputs. However, this sug-

[24] We thank the authors for making the data available to us.

gests that suppliers are small with respect to customers. There is no significant difference in the share that specific and non-specific suppliers represent in firms' cost of goods sold across our three measures of input specificity. Finally, suppliers are located on average a little over 1,100 miles away from their customers, irrespective of whether they are specific or not.

The last part of Panel A compares the size, age, and return on assets of eventually treated and never treated firms.[25] Eventually treated firms – those having one supplier hit by a major disaster at least once during the sample period – are larger, older, and slightly more profitable than never treated firms. This makes it all the more important to ensure in the empirical analysis that firm-level characteristics are not driving the results.

Panel B presents the supplier sample, which consists of 92,977 firm-quarters between 1978 and 2010. There are 4,112 firms in this sample. A firm is included in the sample in each quarter between the first and last year it reports another firm as a customer in the Compustat Segment files. These firms report an average of 1.2 customers. The main variable of interest is the growth in sales over the following four quarters. The sample average for this variable is 15.8%, and the median is 3.9% . The probability that a firm in this sample is hit by a natural disaster in any quarter is 1.5%. The probability that one of a firm's customers is hit in any given quarter is 1.2%. Finally, the probability that one of its customers' suppliers is hit is 7.1%.

[25]Size is defined as total assets (Compustat item AT). Age is defined as the number of years since incorporation; when the date of incorporation is missing, age is defined as the number of years since the firm has been in the Compustat database. Return on assets (ROA) is operating income before depreciation and amortization (item OIBDP) divided by total assets.

4. Results

4.1. Effect on affected suppliers

We first explore the extent to which suppliers' production is affected when the county where their headquarters are located is hit by a natural disaster.[26] As already discussed, we have no way to formally pin down the channel through which natural disasters translate into disruptions to suppliers' production functions. Instead, we consider their effect on firms' sales.

In our sample of suppliers, we regress firms' sales growth (relative to the same quarter in the following year) on a series of dummies indicating whether a major natural disaster hits the firm in each of the previous three quarters (t-3, t-2, t-1), the current quarter (t), and each of the following four quarters (t+1, t+2, t+3, t+4), as well as fiscal-quarter, year-quarter and firm fixed effects. The results are presented in Table 3. In column (1), the coefficient on the dummies indicating that a disaster hits the firm in the following three quarters are negative and significant, ranging from 3.6 to 5.4 percentage points, which indicates that suppliers' sales growth drops significantly for three consecutive quarters following a disaster. The coefficient on *Disaster hits firm (t+4)* is small and insignificant, indicating that suppliers' sales growth is affected only *after* the passage of a major disaster. Finally, the coefficients on *Disaster hits firm (t-1)*, *Disaster hits firm (t-2)* and *Disaster hits firm (t-3)* are small and insignificant which indicates that the effect on sales growth eventually vanishes. We introduce controls for size, age and profitability interacted with year-quarter fixed effects in column (2). The coefficients' range does not change, which suggests that differences in the types of firms that are hit do not drive the patterns in sales growth. In columns (3) and (4), we introduce industry×year fixed effects and state×year fixed effect. The effect goes

[26] It is important to note that the effect of a natural disaster on production could go *a priori* either way, since the destruction triggered by disasters sometimes generate a local increase in demand (Bernile et al., 2013). Anecdotal evidence indeed suggests that providers of basic supplies experience boosts in sales in the period around the disaster (see e.g. Bloomberg, August 26, 2011, "Home Depot, Lowe's stocks get hurricane boost.")

down slightly in magnitude but remains significant. Taken together, the results suggest that relative to firms in the same state or the same industry, firms with headquarters located in a county directly affected by the natural disaster seem to do worse.

One purpose of the following section is to assess whether suppliers' specificity is a driver of the propagation of firm-level shocks. However, if shocks to specific suppliers were on average larger than shocks to non-specific suppliers, this would lead us to mechanically overestimate the effect of input specificity on the propagation of shocks. We check in Table 4 that the disruption caused by natural disasters is not larger for specific than for non-specific suppliers. To do so, we consider the sample of suppliers and regress firms' sales growth on a dummy indicating whether the firm is hit by a disaster (in the current or following three quarters), as well as a dummy taking the value of one if the firm which is hit is a specific one. We run the same regression for our three measures of input specificity. The coefficient on the interaction term is always positive, although generally not statistically significant, which suggests that shocks to specific suppliers are, if anything, of smaller magnitude than shocks to non-specific suppliers.[27]

4.2. Downstream propagation: effect on customers' sales

In this section, we estimate the effect on firms' sales of shocks affecting their suppliers. We first illustrate the results in Figure 4, which compares the growth in sales (relative to the same quarter in the following year) at different quarters surrounding a major natural disaster for both directly affected suppliers and their customers. The graph highlights that input disruptions translate into lost sales for the firm a few quarters after the supplier is hit.

Baseline results. We then run the OLS panel regression detailed in Section 2, Equation 1, and present the results in Table 5. In Panel A, we consider the effect of input disruption

[27] The coefficient DIFF firm is omitted in columns (1) and (2) because firms' industry classification is fixed over time, and is therefore absorbed by firm fixed effects.

on sales growth. The variable of interest is the dummy *Disaster hits one supplier (t)* which takes the value of one if (at least) one of the firm's suppliers is hit by a natural disaster in quarter t, and zero otherwise. The estimates in column (1) indicate that sales growth drops by 2.9 percentage points. Given the sample mean of 9%, the estimate is economically large. In column (2), we introduce controls for lagged size, age, and profitability, interacted with year-quarter fixed effects. The estimate decreases slightly to 2.3 percentage points and remains significant. In column (3), we add industry×year fixed effects. The point estimate is 2 percentage points, which suggests that the effect is not driven by an industry-wide shock. In column (4), we control for state×year fixed effects and obtain similar results. This confirms that the effect of input disruption on sales is not related to temporary shocks at the state level, or to the fact that treated firms might be closer to the disaster zone than other firms. Across specifications, the coefficient on the dummy *Disaster hits firm* is negative, which reflects the finding presented in Table 3. Similar results are obtained in Panel B, when we replace the dependent variable with the growth in the cost of goods sold. Altogether the results indicate that disruptions to their suppliers' production strongly affect firms' sales growth, which drops by a little over 20% with respect to the sample average. Since suppliers in the sample represent approximately 3% of firms' cost of goods sold, these estimates are strikingly large.

The drop in sales growth should show no prior trends and should be temporary, in order for the parallel trends assumption to be satisfied. As their suppliers restore their productive capacity, firms' sales growth should recover. To test whether this is indeed the case, we analyze the dynamics of the effects. We regress the firm's sales growth on dummies indicating whether a major disaster hits (at least) one of their suppliers in each of the previous three quarters (t-3, t-2, t-1), the current quarter (t), and each of the following four quarters (t+1, t+2, t+3, t+4). The results presented in Table 6 indicate that the coefficient in the current quarter (*Disaster hits one firm (t)*) is the largest in absolute value. The dummies *Disaster hits one supplier (t+3)* and *Disaster hits one supplier (t+4)* allow us to assess whether an effect on firms' sales growth is found contemporaneously or prior to the quarter when the effect of natural disasters is found on suppliers (which occurs in (t+3), see Table 3). We find that, across all specifications, both coefficients are economically and statistically insignificant. This confirms that the drop in firms' sales growth is not driven by prior trends, but that it is indeed *caused* by the natural disaster affecting one of its suppliers.

We go one step further to test the validity of the parallel trend assumption. We check whether eventually treated firms and never treated firms experience diverging time trends in the absence of major natural disasters. To do so, we regress firms' sales growth on a treatment dummy which equals one for firms eventually treated in our sample interacted with the full set of year-quarter fixed effects, $T_i \times \delta_t$, and estimate the regression only over periods for which no major natural disaster has hit the U.S. territory in the previous, current or following three quarters. The regression also includes fiscal-quarter fixed effects and firm fixed effects. We are mainly interested in the F-statistics of the joint significance test of all the $T_i \times \delta_t$ (see column (5)). If we fail to reject the null hypothesis that they all equal zero, this would provide strong support for the parallel trend assumption. Results are reported in Table 7. In all cases, F-tests are small, and we always fail to reject at conventional levels the null hypothesis that all $T_i \times \delta_t$ are zero in the absence of major natural disasters. This makes us confident that *never treated* firms provide a good counterfactual for *eventually treated* firms in periods of major natural disasters.

One might be concerned that the results are driven by the location of customers' plants close to the headquarters of their suppliers. In Panel A, Table 8, we introduce a dummy taking the value of one if more than 10% of the customer's workforce across all establishments is hit by a natural disaster. If headquarters' locations are poor proxies for the true location of customers' establishments, and if the economic link with the supplier proxies for the true location of the customer, this variable should absorb the effect. The results indicate that this is not the case, as the coefficient on *Disaster hits a supplier* remains remarkably stable (compared to Table 5) and statistically significant in all specifications.[28]

Another concern is that the estimates from Table 5 might reflect common demand shocks affecting the firm and its suppliers, for instance because their customer base is located in the same area. To handle this issue, we augment our OLS regressions with a dummy called *Disaster hits any eventually linked suppliers' location* which takes the value of one if any of all the headquarters' county locations of all suppliers once in a relationship with the firm is hit by a natural disaster. If the effects that we are picking up in Table 5 reflect common demand shocks, this variable should subsume the main variable of interest, *Disaster hits one supplier*. This is arguably a very conservative test of our hypothesis, since it is likely that some of the supplier-customer relationships that we observed from the SFAS No. 131 were initiated earlier (at a time where the customer represented less than 10% of the suppliers' sales) or maintained later on. We present the results of this specification in Panel B, Table 8. The coefficient on the additional variable is insignificant, while the coefficient on *Disaster hits one supplier* remains stable and significant in all specifications. Hence, input disruptions caused by natural disasters propagate only when there is an active business relationship between the disrupted supplier and the firm.

Inventories. The propagation of input shocks should be stronger when the firm held less inventories in the quarter prior to the disaster. To test whether this is indeed the case, we analyze the dynamics of the effects separately for firms holding few and a lot of inventories in the previous quarter (t-1). The results are presented in the Appendix, Table A.2. As expected, the effect of input disruptions on sales growth is mitigated when firms held more inventories.

[28]The results are similar when instead of a 10% threshold, we use a 1, 2, or 5% threshold. They are also similar when we restrict the sample to firm-years for which establishment data are available, from 1997 to 2010.

Input specificity. The propagation of input shocks should be stronger when the supplier is specific, and thus harder for the firm to replace. We use our three measures of specificity to test whether this is the case. To do so, we run the augmented model detailed in Section 2, Equation 2. We expect the coefficient on the dummy *Disaster hits one specific supplier* to be positive, significant, and larger than the dummy on the coefficient *Disaster hits one non-specific supplier*. The results are presented in Table 9. Overall, the effect is indeed much stronger when a disaster hits a specific supplier rather than a non-specific one. The effect of non-specific suppliers is insignificant, whereas the effect of specific suppliers is greater than the baseline estimates. Hence, the results suggest that input specificity is a key driver of the propagation of shocks from suppliers to their customers.

Suppliers' size. We then investigate whether the effect of input disruption varies with the relative size of affected suppliers. Going back to the theoretical framework presented in Section 1, if intermediate inputs are strong complements, the effect of input disruptions should not depend on the importance of affected suppliers in firms' production. We augment the baseline regression with the dummy *Disaster hits one large supplier* in columns (1) and (2) of Table A.3, and with the dummy *Disaster hits more than one supplier* in columns (3) and (4). In both cases, we find that the coefficient is negative, but low and insignificant. Hence, the effect of input disruptions on sales growth is larger when relatively larger suppliers are affected, but not significantly so, which suggests that intermediate inputs are indeed strong complements.

Robustness. Finally, we perform a set of robustness tests and present the results in the Appendix. We first want to check that our results are not driven by large natural disasters, which would affect customers in our sample through their aggregate effect on the U.S. economy. To do so, we interact the dummy *Disaster hits one supplier* with the variable *Large nb of affected firms*, which takes the value of one for disasters that lie in the top half of the distribution of the total number of directly affected Compustat firms. The results are reported in columns (1) and (2) of Table A.4. The coefficient on the interaction term is positive and insignificant, indicating that the effect of input disruption does not vary with the importance of disasters – if anything, it is smaller for more important ones. We also look at whether the results differ for exporters and non-exporters. To do so, we interact the dummy *Disaster hits one supplier* with the variable > 25% *sales abroad*, which takes the value of one if the customer firm reports sales abroad that represent more than 25% of its total sales in the two years prior to any given quarter. As shown in columns (3) and (4), we find that the effect or the treatment is virtually the same for exporters and non-exporters, indicating again that the results are driven by input disruptions rather than demand effects due to natural disasters on the U.S. economy.

We have shown above that when we control for the location of firms' headquarters and establishments. It remains the possibility that the exclusion restriction assumption might be violated for natural disasters events that affect suppliers and customers jointly, though there are very few observations in that case in our sample. Still, we show in Panel A of Table A.5 that our results remain virtually the same when we restrict the sample to customer-supplier relationships where both parties are never jointly affected by a natural disaster over the whole sample period. We perform an additional robustness test to address the possibility of diverging time trends between control and treated groups which consists of estimating the difference-in-differences specification using only observations of eventually treated firms. We show in Panel B of Table A.5 that our results are similar to those in Table 5 when we restrict the sample to eventually treated customer firms.

Firms with more suppliers are mechanically more likely to have one supplier hit by a natural disaster. We augment the baseline regression with dummies indicating terciles of the number of firms' suppliers in Panel A of Table A.6; in Panel B, we interact controls for the number of firms' suppliers interacted with year-quarter fixed effects. In both cases, the estimates remain stable, which indicate that the results are driven by the treatment rather than the number of firms' links. Finally we check in Table A.7 that our results are robust to an alternative definition of our main dependent variable, namely the difference in the logarithm of firm sales.

4.3. Downstream propagation: effect on customers' value

The drop in sales growth could simply reflect the fact that sales are delayed, which would have few consequences for firms' cash flows and value. However, the estimates in Table 6 indicate that firms' sales growth does not overshoot in the quarters following disasters, suggesting that these sales are lost indeed. We go one step further and ask whether the disruption to specific suppliers is reflected in firms' stock returns. We follow standard event study methodology, and consider the first day when a given major disaster hits a county in which a linked supplier's headquarters is located. Under the efficient market hypothesis, the news of input disruption should be quickly reflected in the firm share price, allowing us to compute the associated drop in firm value.

Empirical methodology. We select all firm-disaster pairs in our sample satisfying the following requirements: (i) (at least) one supplier of the firm is hit by the disaster, (ii) the firm is not hit by the disaster, (iii) the firm and its suppliers are not hit by another major disaster in the previous or following 30 trading days around the event date, and (iv) the firm has no missing daily returns in the estimation or event window. The event date is the day considered as the beginning of the disaster in the SHELDUS database.[29] We find 1,039 events satisfying the above requirements. For each firm-disaster pair, we then estimate daily abnormal stock returns using the Fama-French-Carhart four-factor model:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + s_i\ SMB_t + h_i\ HML_t + u_i\ UMD_t + \epsilon_{i,t} \tag{4}$$

[29] If the day reported as the beginning of the disaster in SHELDUS is a non-trading day, we use the next trading day as the event date. If more than one supplier is hit by the same disaster, the earliest beginning date in SHELDUS is considered as the event date.

where $R_{i,t}$ is the daily return of firm i; $R_{M,t}$ is the daily return of the market portfolio minus the risk-free rate; SMB_t is the daily return of a small-minus-big portfolio, HML_t is the daily return of a high-minus-low portfolio, UMD_t is the daily return of an up-minus-down portfolio.[30] The four-factor model is estimated over the interval from 260 to 11 trading days before the event date. We use the estimates of the model $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{s}_i$, $\hat{h}_i$, $\hat{u}_i$ to construct abnormal returns in the event window as:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{M,t} + \hat{s}_i SMB_t + \hat{h}_i HML_t + \hat{u}_i UMD_t) \quad (5)$$

We then aggregate daily abnormal stock returns by averaging them over all firm-disaster pairs (N) and summing them over the trading days of different event windows – $[-10, -1]$, $[0, 10]$, $[11, 20]$, $[21, 30]$, and $[-10, 30]$ where $[t_0 = -10, T = 30]$ is a 41 trading days window starting 10 trading days before the event date – to obtain cumulative average abnormal returns (CAAR). Formally,

$$CAAR = \sum_{t=t_0}^{T} \left(\frac{1}{N} \sum_{i=1}^{N} AR_{it}\right)$$

We also examine whether the effect on firms' stock returns differs with the *specificity* of affected suppliers. To do so, we compute firms' cumulative abnormal returns separately for natural disasters affecting or not (at least) one specific supplier.

Since natural disasters hit several firms at the same time, this is likely to generate cross-sectional correlation in abnormal returns across (indirectly affected) customer firms. In order to address this issue, we test for statistical significance using the ADJ-BMP t-statistic proposed by Kolari and Pynnönen (2010), which is a modified version of the standardized test developed in Boehmer et al. (1991). Kolari and Pynnönen (2010) show that the ADJ-BMP test accounts for cross-sectional correlation in abnormal returns and is robust to serial correlation.[31]

[30] R_M, SMB, HML, and UMD returns are obtained from Kenneth French's website. SMB, HML, and UMD returns are meant to capture size, book-to-market, and return momentum effects, respectively.

[31] Note also that simulations presented in Kolari and Pynnönen (2010) suggest that the ADJ-BMP test is superior in terms of power to the commonly used portfolio approach to account for serial correlation.

Results. Table 10, illustrated in Figure 5, reports cumulative average abnormal returns over different event windows – as well as their respective ADJ-BMP t-statistics – separately for treated firms, their (directly affected) suppliers, as well as untreated firms, i.e., for which all linked suppliers are not affected by a given major disaster. In robustness tests presented in Tables A.8 and A.9 in the Appendix, we report the results when abnormal returns are estimated with the three-factor model of Fama and French (1993). CAAR for treated customer firms on the 41 trading days event window $[t_0 = -10, T = 30]$ are negative and statistically significant, indicating a drop of around 1% in the firm stock price when one of its supplier(s) is hit by a major natural disaster. Virtually all of this drop occurs in the 21 trading days $[t_0 = 0, T = 20]$ following the event, for which CAAR are highly statistically significant, which is consistent with investors quickly reacting to the news. These findings indicate that firms' sales are not simply postponed in reaction to input disruptions, but materialize into sizable value losses.

We find that directly affected suppliers experience an abnormal drop in returns of around 2.4% over the same event window. We also observe a negative, although not statistically significant effect in the 10 trading days before the event.[32] In the third column of Table 10 we consider the average stock price reaction of *untreated* customers. Reassuringly, the size of the effect is small in all event windows for these firms.

Finally, Table 11 presents the results separately for events affecting specific and non-specific suppliers. For our three measures of input specificity, we obtain very similar findings: firms experience an economically and statistically significant drop in returns only when disasters hit their *specific* suppliers (ranging between -1.3 and -2.6% depending on the measure of input specificity).

Overall, these findings indicate that stock prices react to supplier risk, especially when

[32] Earthquakes' striking dates might be considered truly unexpected events. However, with hurricanes for instance, stock price valuation might incorporate forecasts about the passage and severity of the hurricane in the few days prior to the striking date. Still, such adjustments should be relatively small in comparison with the news revealed from the day on which the hurricane strikes, regarding the *actual* damages incurred by suppliers.

linked suppliers are specific. These findings provide, to the best of our knowledge, the first cleanly identified evidence that input disruptions have an effect on firm value, and that input specificity is a key determinant thereof.

If input shocks to firms' production are driving the results on customer stock prices, it should be true that a larger drop in abnormal returns for customer firms predicts a larger drop in their sales growth. We test this hypothesis by regressing customer firms' sales growth relative to the same quarter in the following year on their estimated cumulative abnormal results (CAR) around the first day of a natural disaster affecting (at least) one of their suppliers. Table 12 presents the results. Reassuringly, we find a robust relationship between CAR and future sales growth: an abnormal decrease in returns in the few days following an event affecting one of the firm's suppliers is associated with a decrease in sales growth relative to the following year.

4.4. Horizontal propagation: effect on related suppliers

In this section, we explore whether the effects documented above spill over to other related suppliers, which are not *directly* affected by the natural disaster, but only *indirectly* through their common relationship with the same customer. Going back to the setting described in Section 2, we are interested in the response of S2 to the drop in C's sales triggered by a disruption to S1's production. As discussed in Section 1, the direction of the effect is unclear. If intermediate inputs are substitutes, other suppliers might experience a boost in sales. By contrast, if intermediate inputs are strong complements, related suppliers might experience a decrease in sales, in particular if they cannot easily shift to other customers. To estimate the direction of the effect, we run the OLS regression presented in Equation (3). The coefficient of interest is *Disaster hits a customer's supplier*, which indicates whether a supplier's customer has at least one other supplier hit by a natural disaster in a given quarter.

The results are presented in Table 13. In column (1), the coefficient on *Disaster hits* *one customer's supplier* is a negative and significant 2.8 percentage point decrease in sales growth. This is consistent with substantial negative spillovers to related suppliers. In line with Table 3, the coefficient on *Disaster hits firm (t,t+3)* is also negative and significant. Results presented in columns (2) to (4) are obtained by augmenting the model with a dummy, *Disaster hits one customer's specific supplier*, which isolates the effect of disruptions to specific suppliers of the customer. The estimates indicate that most of the negative effect feeding back from the customer comes from initial shocks to specific suppliers (either differentiated, R&D-intensive, or patent-intensive). These results uncover an important channel through which firm-specific shocks propagate horizontally, across suppliers of a given firm.

These effects may be driven by the fact that some establishments of S2 are located close to S1. In order to address this concern, we introduce a dummy equal to one if at least 10% of S2's workforce is hit by the disaster. If the effect that we are measuring in Table 13 is due to the fact that the link between S1 and S2 proxies for the location of S2's plants, then this variable should absorb the effects of our main treatment variable. In Panel A, Table 14, the introduction of this dummy does not affect the coefficient on *Disaster hits one customer's supplier*.

Another concern might be that these results are driven by unobserved economic links between S1 and S2, not related to their common relationship with C. The fact that S2's sales growth is affected when S1 is hit by a natural disaster could be the consequence of the fact that S2's demand is located close to the headquarters of S1 and is therefore affected by the disaster. In Panel B, Table 14, we augment the model with a dummy called *Disaster hits any customers' eventually linked suppliers' location* which takes the value of one if for any customer of S1, at least one of all the locations of all suppliers once in a relationship with this customer is hit by a natural disaster. If the effects that we are picking up in Table 13 reflect the geographical clustering of the demand to suppliers of C, this variable should subsume the main variable of interest. However, we find that the results are robust to the introduction of this variable.

Finally, we check that the effect on S2 is not driven by a common industry shock affecting both S1 and S2 by introducing a dummy called *Disaster hits any eventually linked customer's suppliers* taking the value of one whenever C is affected by a shock to S1, *irrespective* of whether there is an active business relationship between C and S2. If the effects found on S2 are related to common shocks to S1 and S2, the inclusion of this variable should absorb the effect of the variable *Disaster hits one customer's supplier*. However, in Panel C, Table 14, the coefficients are robust to the introduction of this variable. In addition, the coefficient on this variable is not different from zero, which indicates that the initial shock would not spill over to related suppliers in the absence of an active economic link through their common customer.

4.5. Discussion

Is the effect of disruptions in firms' sales growth reflected in sector-wide data, or is it offset in the aggregate? To answer this question, we follow Foerster et al. (2011) and use the Federal Reserve Boards Index of Industrial Production (IP), a quarterly index of real output disaggregated into 233 NAICS sectors. To identify whether the *suppliers* of a given sector are hit by a natural disaster, we use the 2007 input-output table produced by the BEA, disaggregated into 388 NAICS sectors. We consider a sector as a supplier to a downstream sector if it accounts for more than 10% of the intermediate inputs of the downstream sector. We use the 2008 County Business Pattern data from the U.S. Census Bureau to obtain the number of employees per NAICS$\times$county. In each quarter, we compute the proportion of employees in a given sector located in counties which are hit by a natural disaster. We then run similar regressions as those we ran on firm-level data, and present the results in Table A.10. As it turns out, disruptions to specific sectors cause a drop by more than 1 percentage point in the real output growth of downstream sectors.

How economically meaningful is the propagation mechanism that we identify from natural disasters? The economic importance of propagation depends on the relative aggregate output losses for suppliers and customers in our sample. To compute this multiplier, we first estimate the lost sales for each firm in the sample due to direct or indirect exposure to natural disasters. The drop in sales *growth* is obtained for each firm by taking the residual of a regression of sales growth on fiscal-quarter, year-quarter and firm fixed effects, as well as controls for size, age, and return on assets interacted with year-quarter dummies, in the four quarters surrounding any disaster. We then apply these sales growth residuals to the 2013 constant dollar value of firms' sales to obtain the dollar value of lost sales. We aggregate these lost sales across suppliers and customers in our sample. We find that lost sales amount to approximately $103 billion for suppliers, and $366 billion for customers. Hence, $1 of lost sales at the supplier level leads to $3.5 of lost sales at the customer level in our sample. This suggests that relationships in production networks substantially amplify idiosyncratic shocks.

How important are specific intermediate inputs for the average U.S. firm? Figure 6 draws from Nunn (2007) to quantify the importance of input specificity. The author uses the U.S. input-output table to identify which intermediate inputs are used and in what proportions, in the production of each final good. Then, using data from Rauch (1999), inputs are sorted into those sold on an organized exchange, those referenced priced in a trade publication, and those that are differentiated. As evidenced from the graph, the share of differentiated inputs is large and increasing. Hence, the propagation channel examined in this paper is likely to play an important and growing role for the aggregation of idiosyncratic shocks in production networks.

How much can we learn from natural disasters? Our results are informative for these kinds of idiosyncratic shocks and their propagation in the economy. Nonetheless, these results can plausibly be extended to other forms of firm-specific idiosyncratic shocks, such as strikes or management turnover for instance.[33] In addition, the results presented in this paper also extend to the specificity of inputs within the boundaries of the firm. While the customer-supplier links allow us to pin down the nature of the input, we would expect similar

[33]For narrative examples of the role of strikes at the largest U.S. firms in explaining GDP fluctuations, see Gabaix (2011).

results to be obtained within a firm, when the division producing a specific part of the final good is hit by a shock.

Finally, the extrapolation of the results should take into account that firms endogenously select their location, and the location of their suppliers. This does not threaten our identification strategy, and should bias the results against finding any propagation effects. However, it might affect the extent to which we can use these findings to estimate the impact of larger shocks, if firms devote more resources to insure themselves against those than against natural disasters.

5. Conclusion

This paper explores whether firm-level shocks propagate in production networks. Using supplier-customer links reported by U.S. publicly listed firms, we find that customers of suppliers hit by a natural disaster experience a drop of 2 percentage points in sales growth following the event, which amounts to a 20% drop with respect to the sample average. Given the relative size of suppliers and customers in our sample, this estimate is strikingly large. The effect is temporary; it shows no prior trends, and is only observed when the relationship between customers and suppliers is active. It is significantly stronger when the affected supplier produces differentiated goods, has a high level of R&D, or owns patents and is thus plausibly more difficult to replace. Sales losses translate into significant value losses to the order 1% of market equity value. Finally, the effect spills over to other suppliers, who also experience a drop in sales growth following the disaster.

We provide evidence that, on average, specific input disruptions do not seem to be compensated, and translate into sector-wide output losses. Given that a large share of firms' inputs in the U.S. are specific, the amplification mechanism that we describe is likely to be pervasive. Taken together, these findings suggest that input specificity is a key determinant of the propagation of idiosyncratic shocks in the economy.

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A. Appendix

A.1. Theoretical framework

Suppose that a firm produces a quantity Q with the following standard Cobb-Douglas aggregate of capital, K, labor, L, and an index of intermediate inputs, M:

$$Q = A\ K^{\alpha_K} L^{\alpha_L} M^{\alpha_M}$$

where A is the firm's productivity and $\alpha_K + \alpha_L + \alpha_M = 1$. We assume that capital stock K is fixed. M is a CES aggregate of n intermediate inputs with elasticity of substitution σ:

$$M = \left(\sum_{i=1}^{n} \lambda_i^{\frac{1}{\sigma}}\ q_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where q_i is the quantity of each input $i \in \{1, \ldots, n\}$ used in production and the parameters λ_i indicate the importance of each input i in M.

The firm maximizes the following profit function Π, taking its stock of capital, K, and all prices as given:

$$\max_{L, q_1, \ldots, q_n} \Pi = pQ - rK - wL - \sum_{i=1}^{n} p_i\ q_i$$

where p, w, r, and p_i for $i \in \{1, \ldots, n\}$ are the prices of output, labor, capital, and each intermediate input i, respectively. Let us denote L^*, q_i^* for $i \in \{1, \ldots, n\}$ and Q^* the (unconstrained) optimal associated quantities.

We want to measure the effect on production of a small deviation in the availability of one input – by convention input $i = 1$ – from its first-best level q_1^* to its constrained level $\overline{q}_1 < q_1^*$.

Denoting $\overline{Q}$ the constrained-optimal associated production, $\overline{L}$, and $\overline{q_i}$ for $i \in \{2, \ldots, n\}$ the constrained-optimal demand for labor and for the other $n-1$ inputs, we can compute the linear approximation of the relationship between the firm's output growth rate, $g_Q = \frac{\overline{Q}-Q^*}{Q^*}$, and the disrupted input's growth rate $g_{q_1} = \frac{\overline{q_1} - q_1^*}{q_1^*}$. The following equation, derived below, expresses the relationship between g_Q and g_{q_1} in function of the elasticity of substitution between inputs, σ, and the disrupted input cost share, denoted $s_1 \equiv \frac{p_1 q_1^*}{\sum_{i=1}^n p_i q_i^*}$:

$$g_Q = \frac{\alpha_M}{\alpha_M + \alpha_K(1 + \sigma \frac{1-s_1}{s_1})} \times g_{q_1} \tag{A.1}$$

Equation (A.1) yields g_Q/g_{q_1}, the pass-through rate, i.e., the elasticity of output growth to the drop in the constrained input. g_Q/g_{q_1} is lower than 1, decreasing in σ (because higher substitutability across intermediate inputs means that the constrained input has less effect), increasing in the cost share of the constrained input, s_1, and increasing in the share, σ_M, of the intermediate bundle M in production.

Equation (A.1) delivers one key insight for our analysis. When the constrained input cost share s_1 is small – as it is on average in our sample – the pass-through g_Q/g_{q_1} is small unless inputs are relatively strong complements. In the limit case in which inputs are perfect complements,[34] – i.e., when $\sigma \to 0$ –, the pass-through, $\frac{g_Q}{g_{q_1}}$, does not depend on s_1 and reaches its highest value $\frac{\alpha_M}{\alpha_M + \alpha_K}$.[35]

The simple framework presented above also allows us to write the linear approximation of the relationship between the growth in the disrupted input, g_{q_1}, and the growth of any other unaffected input i, g_{q_i}, as follows:

$$\forall i \in \{2, \ldots, n\}, \; g_{q_i} = \frac{\alpha_M + (1-\sigma)\alpha_K}{\alpha_M + \alpha_K(1 + \sigma \frac{1-s_1}{s_1})} \times g_{q_1} \tag{A.2}$$

The pass-through rate to other inputs, $\frac{g_{q_i}}{g_{q_1}}$, can be either positive or negative depending on the value of the parameters. If intermediate inputs are relatively strong substitutes – that is, if $\sigma > \frac{\alpha_M + \alpha_K}{\alpha_K}$ – the pass-through rate is negative, i.e., the drop in q_1 leads to an increase in the use of other inputs q_i. In sharp contrast, if intermediate inputs are relatively strong

[34] This limit case is the Leontief (1936) production function.

[35] Reasonable estimates of α_M and α_K ($\alpha_M = \frac{1}{2}, \alpha_K = \frac{1}{6}$) obtained from the share of capital and intermediate inputs in total production in the U.S., would yield an estimate of 0.75 for this limit case.

complements – that is, if $\sigma < 1$ – the pass-through rate $\frac{g_{q_i}}{g_{q_1}}$ is positive and larger than $\frac{g_Q}{g_{q_1}}$, the effect on total production.[36] The intuition for this result is the following: first, the elasticity of substitution between the intermediate bundle, M, and labor, L, equals 1 as the production function is a Cobb-Douglas aggregate of capital, labor, and intermediate inputs; it follows that in response to an input shock, when $\sigma < 1$, substitution towards labor (governed by a substitution elasticity equal to 1) outweighs substitution towards other intermediate inputs within M (governed by a substitution elasticity equal to σ), and thus the drop in the use of the other intermediate inputs $i \in \{2, \ldots, n\}$ is relatively larger than the drop in production.

Proof. The first-order conditions of the firm maximization problem yield:

$$pA\alpha_M \lambda_i^{\frac{1}{\sigma}} q_i^{*\frac{-1}{\sigma}} K^{\alpha_K} L^{*\alpha_L} \left(\sum_{i=1}^{n} \lambda_i^{\frac{1}{\sigma}} q_i^{*\frac{\sigma-1}{\sigma}} \right)^{\alpha_M \frac{\sigma}{\sigma-1} - 1} = p_i, \ \forall i \in \{1, \ldots, n\}$$

$$\alpha_L \frac{Q^*}{L^*} p = w$$

The first-order conditions of the firm maximization problem when input 1 is in short supply yield:

$$pA\alpha_M \lambda_i^{\frac{1}{\sigma}} \overline{q_i}^{\frac{-1}{\sigma}} K^{\alpha_K} \overline{L}^{\alpha_L} \left(\sum_{i=1}^{n} \lambda_i^{\frac{1}{\sigma}} \overline{q_i}^{\frac{\sigma-1}{\sigma}} \right)^{\alpha_M \frac{\sigma}{\sigma-1} - 1} = p_i, \ \forall i \in \{2, \ldots, n\}$$

$$\alpha_L \frac{\overline{Q}}{\overline{L}} p = w$$

When combined, the above equations yield:

$$\frac{q_i^*}{q_j^*} = \frac{\lambda_i}{\lambda_j} \left(\frac{p_j}{p_i} \right)^{\sigma} \ \forall i, j \in \{1, \ldots, n\} \tag{A.3}$$

[36]For intermediate values of σ – that is, $1 < \sigma < \frac{\alpha_M + \alpha_K}{\alpha_K}$ –, the pass-through is positive but lower than $\frac{g_Q}{g_{q_1}}$.

$$\frac{L^*}{\overline{L}} = \frac{Q^*}{\overline{Q}} \tag{A.4}$$

$$\frac{q_i^*}{\overline{q}_i} = \left(\frac{L^*}{\overline{L}}\right)^{\sigma\alpha_L} \left(\frac{\sum_{i=1}^n \lambda_i^{\frac{1}{\sigma}} {q_i^*}^{\frac{\sigma-1}{\sigma}}}{\sum_{i=1}^n \lambda_i^{\frac{1}{\sigma}} \overline{q}_i^{\frac{\sigma-1}{\sigma}}}\right)^{\sigma\left(\alpha_M \frac{\sigma}{\sigma-1}-1\right)} \quad \forall i \in \{2, \ldots, n\} \tag{A.5}$$

Moreover, we have:

$$\frac{Q^*}{\overline{Q}} = \left(\frac{L^*}{\overline{L}}\right)^{\alpha_L} \left(\frac{\sum_{i=1}^n \lambda_i^{\frac{1}{\sigma}} {q_i^*}^{\frac{\sigma-1}{\sigma}}}{\sum_{i=1}^n \lambda_i^{\frac{1}{\sigma}} \overline{q}_i^{\frac{\sigma-1}{\sigma}}}\right)^{\alpha_M \frac{\sigma}{\sigma-1}} \tag{A.6}$$

which can be rewritten using (A.4) as:

$$\frac{Q^*}{\overline{Q}} = \left(\frac{\sum_{i=1}^n \lambda_i^{\frac{1}{\sigma}} \left(\frac{q_i^*}{q_1^*}\right)^{\frac{\sigma-1}{\sigma}}}{\sum_{i=1}^n \lambda_i^{\frac{1}{\sigma}} \left(\frac{\overline{q}_i}{q_i^*} \times \frac{q_i^*}{q_1^*}\right)^{\frac{\sigma-1}{\sigma}}}\right)^{\frac{\alpha_M\sigma}{(1-\alpha_L)(\sigma-1)}} \tag{A.7}$$

Combining with (A.3) and rearranging brings:

$$\left(\frac{Q^*}{\overline{Q}}\right)^{\frac{(1-\alpha_L)(\sigma-1)}{\alpha_M\sigma}} \left(\lambda_1 p_1^{1-\sigma} \left(\frac{\overline{q}_1}{q_1^*}\right)^{\frac{\sigma-1}{\sigma}} + \sum_{i=2}^n \lambda_i p_i^{1-\sigma} \left(\frac{\overline{q}_i}{q_i^*}\right)^{\frac{\sigma-1}{\sigma}}\right) = \sum_{i=1}^n \lambda_i p_i^{1-\sigma} \tag{A.8}$$

Denoting $s_1 \equiv \frac{p_1 q_1^*}{\sum_{i=1}^n p_i q_i^*}$, the disrupted input cost share, and manipulating (A.3) yields:

$$\frac{1-s_1}{s_1} = \sum_{i=2}^n \frac{\lambda_i}{\lambda_1} \left(\frac{p_i}{p_1}\right)^{1-\sigma} \tag{A.9}$$

Combining (A.4), (A.5) and (A.6) yields for all $i \in \{2, \ldots, n\}$:

$$\frac{q_i^*}{\overline{q}_i} = \left(\frac{Q^*}{\overline{Q}}\right)^{\sigma + \frac{(1-\alpha_L)(1-\sigma)}{\alpha_M}} \tag{A.10}$$

Finally, substituting (A.9) and (A.10) into (A.8), replacing $1-\alpha_L$ by $\alpha_M + \alpha_K$, and rearranging brings:

$$\left(\frac{Q^*}{\overline{Q}}\right)^{\frac{(\alpha_M+\alpha_K)(\sigma-1)}{\alpha_M\sigma}}\left(\left(\frac{\overline{q}_1}{q_1^*}\right)^{\frac{\sigma-1}{\sigma}}+\frac{1-s_1}{s_1}\left(\frac{Q^*}{\overline{Q}}\right)^{(1-\sigma)(1+\frac{(\alpha_M+\alpha_K)(1-\sigma)}{\alpha_M\sigma})}\right)=\frac{1}{s_1} \tag{A.11}$$

Denoting $g_Q=\frac{Q^*-\overline{Q}}{Q^*}$ and $g_{q_1}=\frac{q_1^*-\overline{q_1}}{q_1^*}$, (A.11) provides the following linear approximation for the firm's output growth:

$$g_Q=\frac{\alpha_M}{\alpha_M+\alpha_K(1+\sigma\frac{1-s_1}{s_1})}\times g_{q_1}$$

Finally, denoting $g_{q_i}=\frac{q_i^*-\overline{q_i}}{q_i^*}$, we obtain the following linear approximation for the other inputs' growth:

$$\forall i\in\{2,\ldots,n\},\ g_{q_i}=\frac{\alpha_M+(1-\sigma)\alpha_K}{\alpha_M+\alpha_K(1+\sigma\frac{1-s_1}{s_1})}\times g_{q_1}$$

A.2. Supplementary tables

Table A.1. Sample Composition

This table presents the industry distribution of firm-quarter observations. Panel A presents the industry distribution of firms in the supplier sample, in the customer sample and in Compustat. In Panel B, firms in the supplier sample are categorized as "Hit" if the county where their headquarters is located is hit by a natural disaster in a given quarter, and "Unaffected" otherwise. Firms in the customer sample are categorized as "Treated" if at least one of the firm's suppliers is located in a county hit by a natural disaster, and "Unaffected" otherwise.

Panel A:	Customer and Supplier Samples					
	Supplier Sample		Customer Sample		All Compustat	
48FF Industry	N	%	N	%	N	%
Agriculture	310	(0.3%)	56	(0.1%)	3145	(0.4%)
Food Products	1642	(1.8%)	1160	(1.9%)	13691	(1.9%)
Candy & Soda	140	(0.2%)	97	(0.2%)	1326	(0.2%)
Beer & Liquor	89	(0.1%)	509	(0.8%)	2373	(0.3%)
Tobacco Products	152	(0.2%)	154	(0.3%)	700	(0.1%)
Recreation	1567	(1.7%)	409	(0.7%)	6633	(0.9%)
Entertainment	676	(0.7%)	361	(0.6%)	15167	(2.1%)
Printing and Publishing	309	(0.3%)	730	(1.2%)	6440	(0.9%)
Consumer Goods	2353	(2.5%)	1162	(1.9%)	14312	(2.0%)
Apparel	2476	(2.7%)	414	(0.7%)	10862	(1.5%)
Healthcare	444	(0.5%)	688	(1.1%)	14150	(1.9%)
Medical Equipment	3098	(3.3%)	1640	(2.7%)	25088	(3.4%)
Pharmaceutical Products	7561	(8.1%)	4052	(6.7%)	37505	(5.1%)
Chemicals	1713	(1.8%)	2457	(4.0%)	14330	(2.0%)
Rubber and Plastic Products	1698	(1.8%)	333	(0.5%)	8364	(1.1%)
Textiles	1214	(1.3%)	120	(0.2%)	5629	(0.8%)
Construction Materials	1768	(1.9%)	1046	(1.7%)	17818	(2.4%)
Construction	590	(0.6%)	407	(0.7%)	10512	(1.4%)
Steel Works Etc	1179	(1.3%)	1272	(2.1%)	11422	(1.6%)
Fabricated Products	316	(0.3%)	95	(0.2%)	3365	(0.5%)
Machinery	3504	(3.8%)	1778	(2.9%)	26107	(3.6%)
Electrical Equipment	1949	(2.1%)	951	(1.6%)	12322	(1.7%)
Automobiles and Trucks	2153	(2.3%)	1425	(2.3%)	11272	(1.5%)
Aircraft	1200	(1.3%)	987	(1.6%)	3914	(0.5%)
Shipbuilding, Railroad Equipment	177	(0.2%)	175	(0.3%)	1573	(0.2%)
Defense	327	(0.4%)	217	(0.4%)	1411	(0.2%)
Precious Metals	246	(0.3%)	161	(0.3%)	5187	(0.7%)
Non-Metallic and Industrial Metal Mining	284	(0.3%)	138	(0.2%)	3782	(0.5%)
Coal	307	(0.3%)	88	(0.1%)	1450	(0.2%)
Petroleum and Natural Gas	7695	(8.3%)	4445	(7.3%)	38510	(5.3%)
Utilities	2989	(3.2%)	6570	(10.8%)	42207	(5.8%)
Communication	4418	(4.8%)	3035	(5.0%)	27346	(3.7%)
Personal Services	387	(0.4%)	389	(0.6%)	8919	(1.2%)
Business Services	9646	(10.4%)	3885	(6.4%)	86341	(11.8%)
Computers	6423	(6.9%)	2993	(4.9%)	32085	(4.4%)
Electronic Equipment	10953	(11.8%)	4170	(6.9%)	43208	(5.9%)
Measuring and Control Equipment	2307	(2.5%)	1121	(1.8%)	17759	(2.4%)
Business Supplies	939	(1.0%)	1062	(1.8%)	10132	(1.4%)
Shipping Containers	304	(0.3%)	330	(0.5%)	2339	(0.3%)
Transportation	2279	(2.5%)	2280	(3.8%)	20556	(2.8%)
Wholesale	2884	(3.1%)	3519	(5.8%)	33243	(4.5%)
Retail	387	(0.4%)	2039	(3.4%)	41806	(5.7%)
Restaraunts, Hotels, Motels	105	(0.1%)	917	(1.5%)	16688	(2.3%)
Almost Nothing	1819	(2.0%)	845	(1.4%)	21257	(2.9%)
Total	92977		60682		732246	

Table A.1. (continued)

Panel B:	Treated vs. Unaffected							
	Supplier Sample				Customer Sample			
	Hit		Unaffected		Treated		Unaffected	
48FF Industry	N	%	N	%	N	%	N	%
Agriculture	3	(0.2%)	307	(0.3%)	1	(0.1%)	55	(0.1%)
Food Products	23	(1.7%)	1619	(1.8%)	10	(0.9%)	1150	(1.9%)
Candy & Soda	2	(0.1%)	138	(0.2%)	1	(0.1%)	97	(0.2%)
Beer & Liquor	1	(0.1%)	89	(0.1%)	20	(1.8%)	489	(0.8%)
Tobacco Products	2	(0.1%)	150	(0.2%)	1	(0.1%)	153	(0.3%)
Recreation	24	(1.8%)	1543	(1.7%)	2	(0.2%)	407	(0.7%)
Entertainment	8	(0.6%)	668	(0.7%)	3	(0.3%)	358	(0.6%)
Printing and Publishing	4	(0.3%)	305	(0.3%)	14	(1.2%)	716	(1.2%)
Consumer Goods	48	(3.5%)	2305	(2.5%)	16	(1.4%)	1146	(1.9%)
Apparel	27	(2.0%)	2449	(2.7%)	7	(0.6%)	407	(0.7%)
Healthcare	6	(0.4%)	438	(0.5%)	14	(1.2%)	674	(1.1%)
Medical Equipment	52	(3.8%)	3046	(3.3%)	20	(1.8%)	1620	(2.7%)
Pharmaceutical Products	119	(8.7%)	7442	(8.1%)	100	(8.8%)	3952	(6.6%)
Chemicals	21	(1.5%)	1692	(1.8%)	50	(4.4%)	2407	(4.0%)
Rubber and Plastic Products	35	(2.6%)	1663	(1.8%)	2	(0.2%)	331	(0.6%)
Textiles	21	(1.5%)	1193	(1.3%)	3	(0.3%)	117	(0.2%)
Construction Materials	16	(1.2%)	1752	(1.9%)	8	(0.7%)	1038	(1.7%)
Construction	8	(0.6%)	582	(0.6%)	1	(0.1%)	407	(0.7%)
Steel Works Etc	11	(0.8%)	1168	(1.3%)	11	(1.0%)	1261	(2.1%)
Fabricated Products	4	(0.3%)	312	(0.3%)	1	(0.1%)	95	(0.2%)
Machinery	50	(3.7%)	3454	(3.8%)	19	(1.7%)	1759	(3.0%)
Electrical Equipment	32	(2.3%)	1917	(2.1%)	7	(0.6%)	944	(1.6%)
Automobiles and Trucks	24	(1.8%)	2129	(2.3%)	47	(4.2%)	1378	(2.3%)
Aircraft	15	(1.1%)	1185	(1.3%)	26	(2.3%)	961	(1.6%)
Shipbuilding, Railroad Equipment	6	(0.4%)	171	(0.2%)	2	(0.2%)	173	(0.3%)
Defense	6	(0.4%)	321	(0.4%)	12	(1.1%)	205	(0.3%)
Precious Metals	1	(0.1%)	246	(0.3%)	1	(0.1%)	160	(0.3%)
Non-Metallic and Industrial Metal Mining	3	(0.2%)	281	(0.3%)	1	(0.1%)	137	(0.2%)
Coal	2	(0.1%)	305	(0.3%)	1	(0.1%)	88	(0.1%)
Petroleum and Natural Gas	147	(10.8%)	7548	(8.2%)	105	(9.3%)	4340	(7.3%)
Utilities	58	(4.3%)	2931	(3.2%)	93	(8.2%)	6477	(10.9%)
Communication	49	(3.6%)	4369	(4.8%)	122	(10.8%)	2913	(4.9%)
Personal Services	11	(0.8%)	376	(0.4%)	6	(0.5%)	383	(0.6%)
Business Services	149	(10.9%)	9497	(10.4%)	66	(5.8%)	3819	(6.4%)
Computers	77	(5.7%)	6346	(6.9%)	47	(4.2%)	2946	(4.9%)
Electronic Equipment	114	(8.4%)	10839	(11.8%)	76	(6.7%)	4094	(6.9%)
Measuring and Control Equipment	32	(2.3%)	2275	(2.5%)	11	(1.0%)	1110	(1.9%)
Business Supplies	15	(1.1%)	924	(1.0%)	12	(1.1%)	1050	(1.8%)
Shipping Containers	5	(0.4%)	299	(0.3%)	3	(0.3%)	327	(0.5%)
Transportation	46	(3.4%)	2233	(2.4%)	42	(3.7%)	2238	(3.8%)
Wholesale	54	(4.0%)	2830	(3.1%)	76	(6.7%)	3443	(5.8%)
Retail	3	(0.2%)	384	(0.4%)	41	(3.6%)	1998	(3.4%)
Restaraunts, Hotels, Motels	1	(0.1%)	105	(0.1%)	15	(1.3%)	902	(1.5%)
Almost Nothing	26	(1.9%)	1793	(2.0%)	15	(1.3%)	830	(1.4%)
Total	1362		91619		1132		59555	

Table A.2. Downstream Propagation – The Role of Inventories

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on dummies indicating whether (at least) one dependent supplier is hit by a major disaster in the previous quarter, the current quarter, and each of the following four quarters separately for firms holding few and a lot of inventories in the previous quarter. Inventories are scaled by total assets. All regressions include dummies indicating whether the firm itself is hit by a major disaster in the previous quarter, the current quarter, and each of the following four quarters, as well as fiscal-quarter, year-quarter and firm fixed effects. Columns (2) and (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$			
	Low inventories		Large inventories	
Disaster hits one supplier (t+4)	-0.004	0.009	0.007	0.007
	(0.013)	(0.013)	(0.013)	(0.013)
Disaster hits one supplier (t+3)	-0.016	-0.014	0.005	0.004
	(0.014)	(0.014)	(0.012)	(0.012)
Disaster hits one supplier (t+2)	-0.018	-0.012	0.008	0.013
	(0.015)	(0.014)	(0.013)	(0.013)
Disaster hits one supplier (t+1)	-0.034**	-0.025*	-0.004	0.002
	(0.015)	(0.014)	(0.012)	(0.012)
Disaster hits one supplier (t)	-0.037***	-0.031**	-0.024*	-0.019
	(0.014)	(0.014)	(0.013)	(0.012)
Disaster hits one supplier (t-1)	-0.019	-0.013	-0.017	-0.013
	(0.016)	(0.016)	(0.012)	(0.013)
Disaster hits firm (t+4)	-0.001	0.002	-0.007	-0.009
	(0.021)	(0.021)	(0.015)	(0.015)
Disaster hits firm (t+3)	-0.034*	-0.032*	0.011	0.007
	(0.018)	(0.019)	(0.016)	(0.016)
Disaster hits firm (t+2)	-0.049**	-0.040**	-0.020	-0.020
	(0.020)	(0.020)	(0.016)	(0.016)
Disaster hits firm (t+1)	-0.059***	-0.050***	0.002	0.004
	(0.018)	(0.018)	(0.017)	(0.017)
Disaster hits firm (t)	-0.028	-0.026	-0.015	-0.011
	(0.021)	(0.021)	(0.013)	(0.013)
Disaster hits firm (t-1)	-0.034	-0.034	-0.010	-0.005
	(0.021)	(0.022)	(0.013)	(0.012)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	No	Yes
Observations	28650	28650	28713	28713
R^2	0.280	0.321	0.273	0.311

Table A.3. Downstream Propagation – Size of Affected Suppliers

Disaster hits one large supplier is a dummy equal to one if a disaster hits one supplier that lies in the top half of the yearly distribution of the ratio of the sales of the supplier to the firm (variable SALECS in the Compustat Segment files) over the firm's cost of goods sold. *Disaster hits more than one supplier* is a dummy equal to one if (strictly) more than one of the firm's suppliers is hit by a disaster. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) and (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$			
Disaster hits one large supplier (t)	-0.003	-0.003		
	(0.015)	(0.015)		
Disaster hits more than one supplier (t)			-0.006	-0.007
			(0.017)	(0.018)
Disaster hits one supplier (t)	-0.027**	-0.021*	-0.027***	-0.021**
	(0.013)	(0.012)	(0.010)	(0.010)
Disaster hits firm (t)	-0.023**	-0.018	-0.023**	-0.018
	(0.012)	(0.012)	(0.012)	(0.012)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	No	Yes
Observations	60682	60682	60682	60682
R^2	0.256	0.287	0.256	0.287

Table A.4. Downstream Propagation – Additional Robustness Tests

Large nb of affected firms is a dummy equal to one for disasters that lie in the top half of the distribution of the number of directly affected Compustat firms. $>$ 25% *sales abroad* is a dummy that equals one if the firm reports sales abroad that represent more than 25% of its total sales in the two years prior to any given quarter. *Disaster hits more than one supplier* is a dummy equal to one if more than one of the firm's suppliers is hit by a disaster. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) and (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$			
Disaster hits one supplier (t) × Large nb of affected firms	0.013	0.007		
	(0.019)	(0.019)		
Disaster hits one supplier (t) × $>$ 25% sales abroad			-0.005	0.001
			(0.014)	(0.014)
Disaster hits one supplier (t)	-0.038**	-0.028*	-0.026**	-0.023*
	(0.016)	(0.016)	(0.013)	(0.012)
Disaster hits firm (t)	-0.023**	-0.018	-0.023**	-0.018
	(0.012)	(0.012)	(0.012)	(0.012)
$>$ 25% sales abroad			-0.041***	-0.027**
			(0.011)	(0.010)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	No	Yes
Observations	60682	60682	60682	60682
R^2	0.256	0.287	0.257	0.288

Table A.5. Downstream Propagation – Subsamples

This table presents variants of the regressions in Table 5. Panel A restricts the sample to customer-supplier relationships for which both firms are never hit by the same disaster over the sample period. Panel B restricts the sample to eventually treated customers. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

Panel A:	Relationships Never Hit Jointly Only Sales Growth $(t, t+4)$			
Disaster hits one supplier (t)	-0.028***	-0.021**	-0.019**	-0.017*
	(0.010)	(0.009)	(0.009)	(0.010)
Disaster hits firm (t)	-0.026**	-0.020	-0.012	-0.009
	(0.012)	(0.012)	(0.012)	(0.011)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60184	60184	60184	60184
R^2	0.252	0.284	0.340	0.334

Panel B:	Eventually Treated Customers Only Sales Growth $(t, t+4)$			
Disaster hits one supplier (t)	-0.029***	-0.026***	-0.021**	-0.022**
	(0.010)	(0.009)	(0.009)	(0.009)
Disaster hits firm (t)	-0.009	-0.011	-0.002	-0.010
	(0.014)	(0.015)	(0.014)	(0.013)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	30052	30052	30052	30052
R^2	0.184	0.234	0.326	0.329

Table A.6. Downstream Propagation – Controlling for Number of Suppliers

This table presents variants of the regressions in Table 5. Panel A includes dummies indicating terciles of the number of firms' suppliers as additional control variables. Panel B includes year-quarter fixed effects interacted with terciles of the number of firms' suppliers. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

Panel A:	Control Variables Sales Growth $(t, t+4)$			
Disaster hits one supplier (t)	-0.025***	-0.021**	-0.018**	-0.018*
	(0.009)	(0.009)	(0.008)	(0.009)
Disaster hits firm (t)	-0.023**	-0.018	-0.010	-0.009
	(0.012)	(0.012)	(0.011)	(0.011)
Number of suppliers (t) (Medium)	0.003	0.002	0.003	0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Number of suppliers (t) (Large)	-0.028***	-0.016**	-0.017**	-0.014*
	(0.008)	(0.008)	(0.008)	(0.008)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60682	60682	60682	60682
R^2	0.257	0.288	0.343	0.337

Panel B:	Heterogeneous Trends Sales Growth $(t, t+4)$			
Disaster hits one supplier (t)	-0.025***	-0.022**	-0.020**	-0.019**
	(0.010)	(0.009)	(0.009)	(0.009)
Disaster hits firm (t)	-0.023*	-0.018	-0.009	-0.008
	(0.012)	(0.012)	(0.011)	(0.011)
Number of Suppliers × Year Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60682	60682	60682	60682
R^2	0.259	0.290	0.345	0.339

Table A.7. Downstream Propagation – Alternative Dependent Variable

This table presents variants of the regressions in Table 5, using the difference in the logarithm of sales as an alternative definition of the dependent variable. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	$\Delta_{t,t+4}$ Ln(Sales)			
Disaster hits one supplier (t)	-0.022***	-0.018**	-0.014**	-0.014*
	(0.008)	(0.008)	(0.007)	(0.008)
Disaster hits firm (t)	-0.025***	-0.020**	-0.011	-0.012
	(0.010)	(0.010)	(0.009)	(0.009)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60619	60619	60619	60619
R^2	0.240	0.271	0.339	0.320

Table A.8. Effect on Firm Value – 3-Factor Model

This table presents CAAR of customer firms around the first day of a natural disaster affecting (at least) one of its suppliers. When more than one supplier is affected by the same natural disaster, the event day is the earliest date across affected suppliers reported in the SHELDUS database. Abnormal returns are computed after estimating, for each firm-disaster pair, a 3-factor Fama-French model over the interval from 260 to 11 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, for which the firm itself is hit by the disaster, or for which the firm or one of its suppliers are hit by another major disaster in the previous or following 30 trading days around the event date are excluded. ADJ-BMP t-statistics, presented in parentheses, are computed with the standardized cross-sectional method of Boehmer et al. (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010). Column (2) reports CAAR of directly hit supplier firms. Column (3) reports CAAR of unaffected customer firms, that is including firm-disaster pairs for which no suppliers reporting the firm as a customer have been hit by the disaster. Computations of abnormal returns follow the same procedure as above. The sample period is from 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively, in two-tailed tests.

	CAAR		
	Customers (N=1039)	Suppliers (Direct effect) (N=1530)	Customers (Control group) (N=6081)
$[-10, -1]$	-0.206	-0.396	-0.246**
	(-0.302)	(-1.081)	(-2.353)
$[0, 10]$	-0.622***	-0.845**	-0.060
	(-3.851)	(-2.523)	(-0.076)
$[11, 20]$	-0.476***	-1.180***	-0.083
	(-2.635)	(-3.154)	(-0.135)
$[21, 30]$	0.034	-0.015	0.186
	(1.010)	(-0.332)	(1.513)
$[-10, 30]$	-1.271***	-2.436***	-0.204
	(-2.852)	(-3.600)	(-0.451)

Table A.9. Effect on Firm Value – Input Specificity
3-Factor Model

This table presents CAAR of customer firms separately for events affecting (at least one) specific supplier or only non-specific suppliers. In column (1), a supplier is considered as specific if it belongs to a 2-digit SIC codes industry producing differentiated goods as defined in Giannetti et al. (2011). In column (3), a supplier is considered specific if its ratio of R&D expenses over sales is above the median in the two years prior to any given quarter. In column (5), a supplier is considered as specific if the number of patents it issued in the previous five years is above the median. Abnormal returns are computed after estimating, for each firm-disaster pair, a 3-factor Fama-French model over the interval from 260 to 11 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, for which the firm itself is hit by the disaster, or for which the firm or one of its suppliers are hit by another major disaster in the previous or following 30 trading days on either side of the event date are excluded. ADJ-BMP t-statistics, presented in parentheses, are computed with the standardized cross-sectional method of Boehmer et al. (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010).

	Customers' CAAR when disaster hits at least one supplier					
Supplier specificity:	DIFF.		R&D		PATENT	
	N=473	N=566	N=497	N=542	N=362	N=677
At least one specific supplier ?	Yes	No	Yes	No	Yes	No
$[-10, -1]$	-0.784	0.277	-0.166	-0.243	-0.132	-0.246
	(-1.514)	(1.130)	(-0.377)	(-0.044)	(-0.088)	(-0.304)
$[0, 10]$	-0.545*	-0.687***	-0.952***	-0.320*	-1.309***	-0.255*
	(-1.776)	(-3.191)	(-3.381)	(-1.848)	(-3.548)	(-1.907)
$[11, 20]$	-0.603	-0.371*	-0.412	-0.536**	-0.557	-0.434**
	(-1.445)	(-1.933)	(-1.237)	(-2.246)	(-1.162)	(-2.357)
$[21, 30]$	-0.121	0.163	-0.103	0.160	-0.683	0.417**
	(0.252)	(0.975)	(-0.001)	(1.235)	(-1.150)	(2.017)
$[-10, 30]$	-2.053**	-0.618	-1.634**	-0.939	-2.680***	-0.518
	(-2.242)	(-1.490)	(-2.372)	(-1.485)	(-2.937)	(-1.176)

Table A.10. Real Output Growth at the Sector Level

This table presents estimated coefficients from panel regressions of the sector's industrial production growth relative to the same quarter in the following year on a dummy indicating whether the sector is hit by a natural disaster in the current or following three quarters, as well as a dummy indicating whether (at least) one of the upstream sectors representing more than 10% of the intermediate inputs of the sector is hit by a natural disaster in the current or following three quarters. In columns (1) to (3), a sector is considered to be hit in a given quarter if more than 1, 5, and 10% of employees in this sector are located in counties that are hit by a disaster in this quarter. Panel A presents the baseline regression. Panel B splits sectors into specific and non-specific sectors. A sector is considered as specific if it belongs to a 2-digit SIC codes industry producing differentiated goods as defined in Giannetti et al. (2011). The sample period is from 1978 to 2010. Standard errors presented in parentheses are clustered at the sector level. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sector real output growth (t,t+4)		
	Panel A: baseline		
Cutoff	1% affected	5% affected	10% affected
Disaster hits supplier (t,t+3)	0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.003)
Disaster hits sector (t,t+3)	0.005*	0.007**	0.005
	(0.003)	(0.003)	(0.003)
Year-quarter FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Observations	25440	25440	25440
R^2	0.372	0.372	0.372
	Panel B: specificity		
Cutoff	1% affected	5% affected	10% affected
Disaster hits specific supplier (t,t+3)	-0.007	-0.013***	-0.012***
	(0.006)	(0.004)	(0.004)
Disaster hits non-specific supplier (t,t+3)	0.003	0.001	0.003
	(0.003)	(0.003)	(0.004)
Disaster hits sector (t,t+3)	0.005*	0.007**	0.005
	(0.003)	(0.003)	(0.003)
Year-quarter FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Observations	25440	25440	25440
R^2	0.372	0.373	0.372

B. Graphs and tables

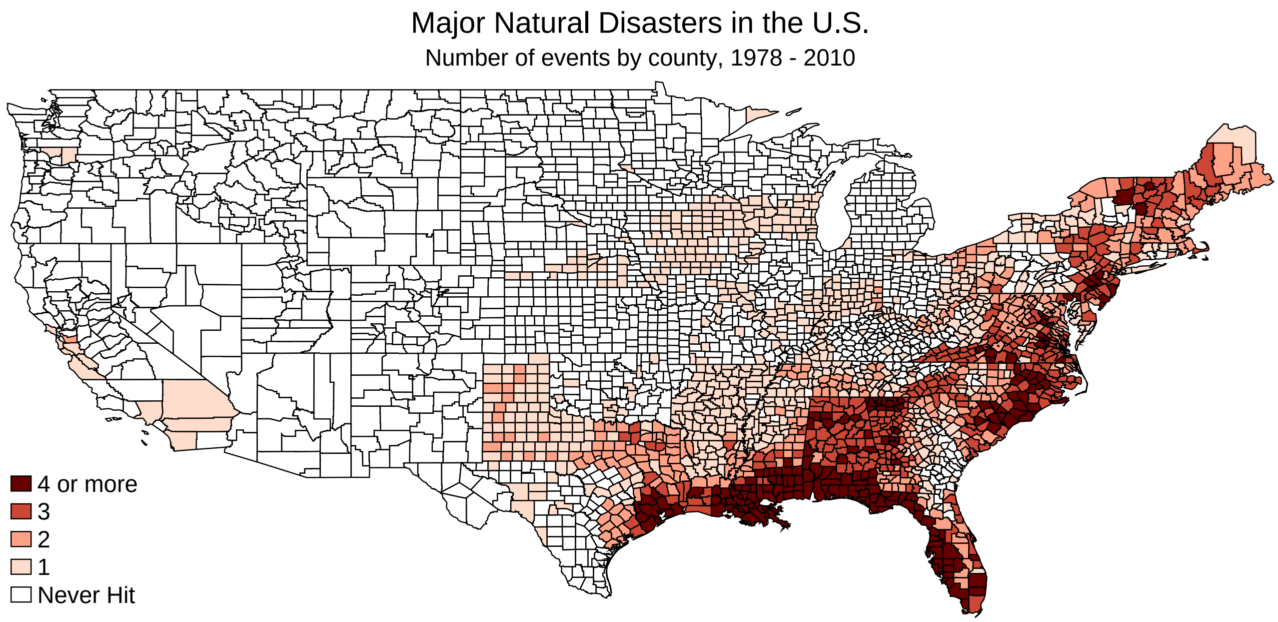

Figure 1. Natural Disasters Frequency by U.S. Counties. This map presents the number of major natural disasters strikes for each county in U.S. mainland over the sample period. The list of counties affected by each major natural disaster is obtained from the SHELDUS database at the University of South Carolina. Table 1 describes the major natural disasters included in the sample.

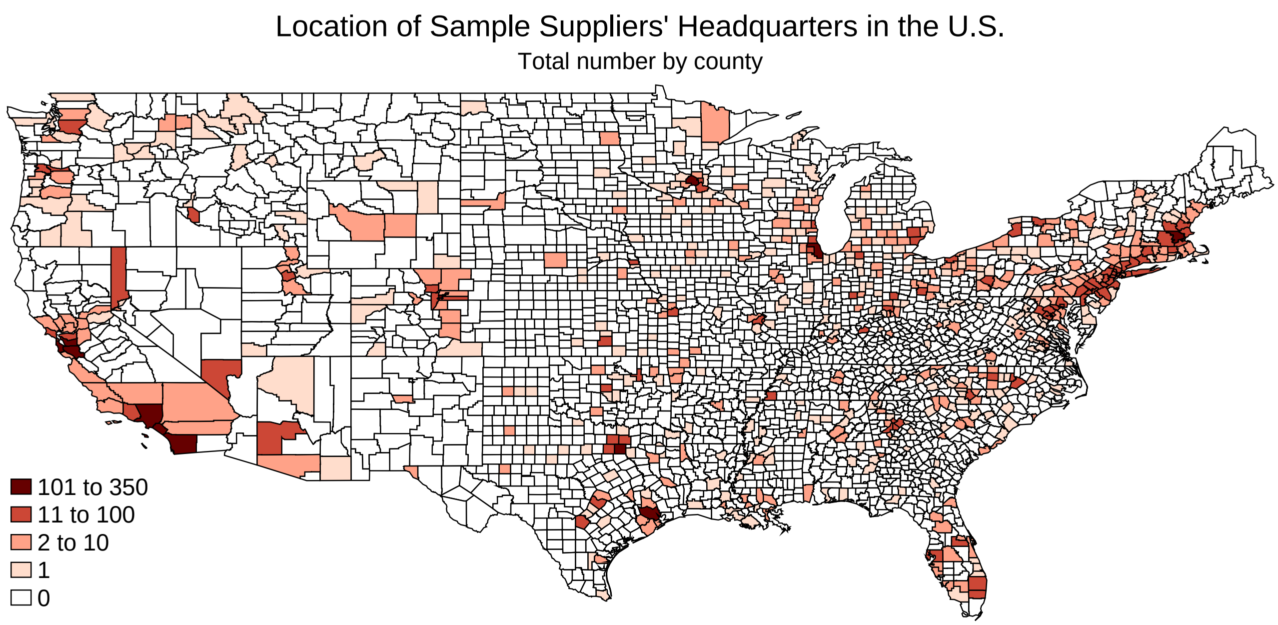

Figure 2. Location of Sample Suppliers' Headquarters. This map presents for our sample the number of suppliers' headquarters located in each U.S. county. Headquarters' locations are obtained from Compustat and Infogroup databases.

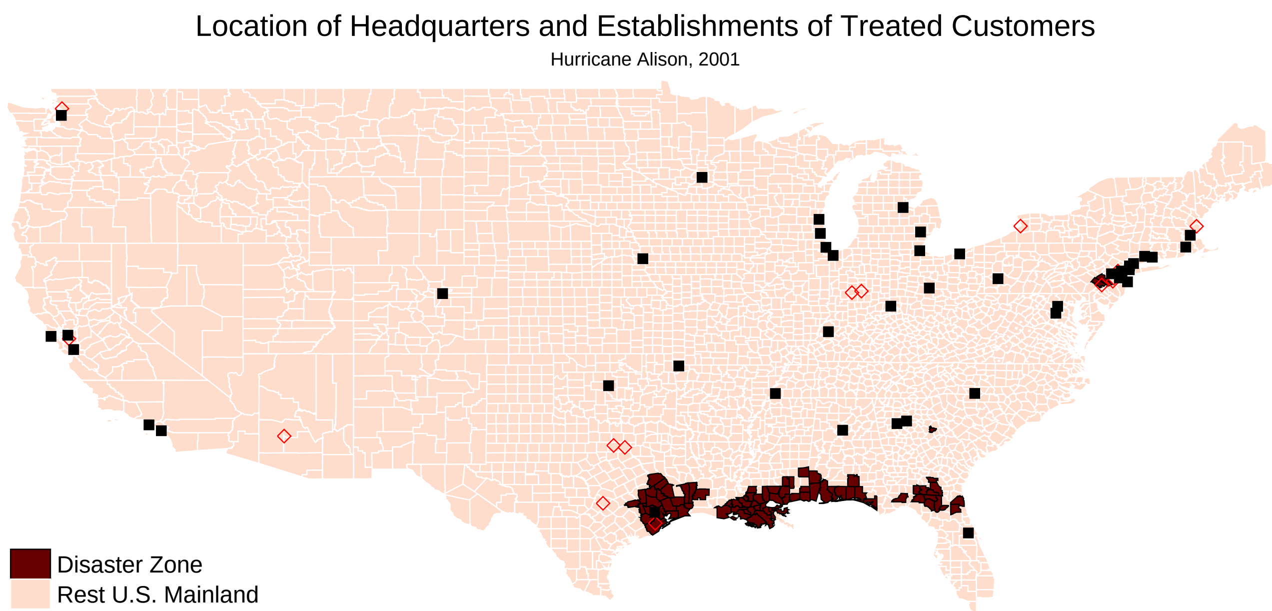

Figure 3. Illustration of Empirical Strategy – Hurricane Alison (2001). This map illustrates our empirical strategy in the context of Hurricane Alison (2001). Counties hit by Hurricane Allison are colored in brown. Rectangles identify the headquarters' location of treated customers; diamonds identify the establishments' (representing more than 10% of firms' total employees) location of treated customers. Data on the location of headquarters and establishments are obtained from Compustat and Infogroup databases. Treated customers are defined as firms linked with (at least) one supplier located in the disaster zone.

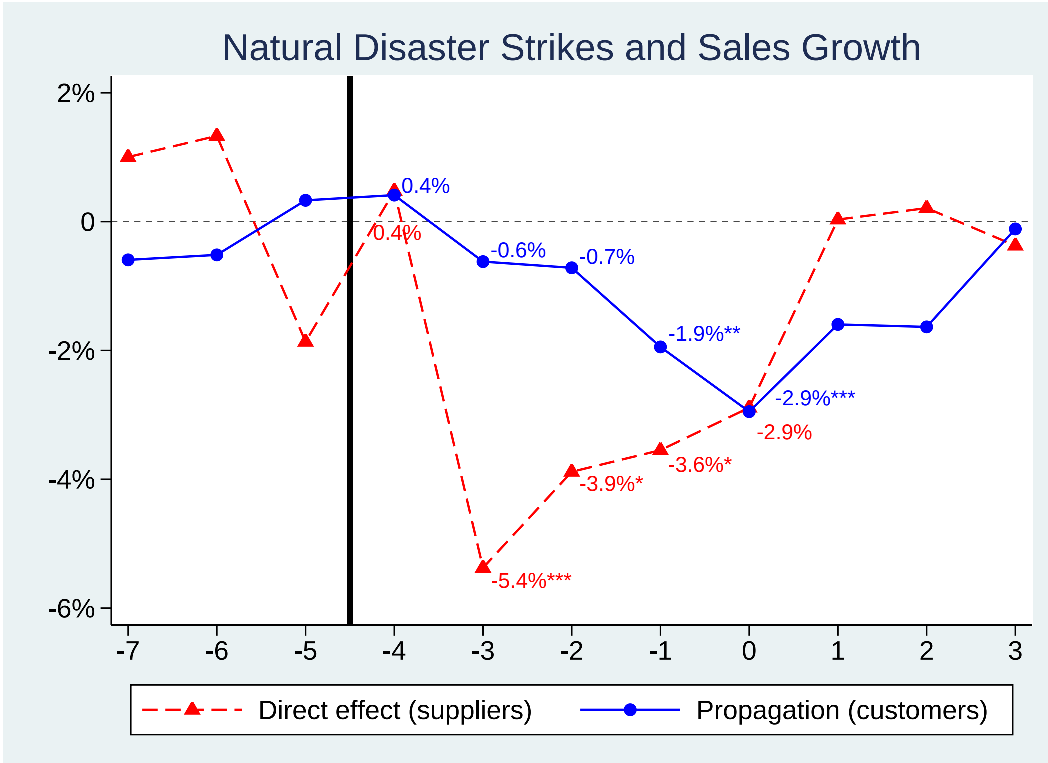

Figure 4. Natural Disaster Strikes and Sales Growth. This figure presents difference-in-differences estimates of sales growth at different quarters surrounding a major natural disaster for both directly affected suppliers and their customers. Sales growth is the growth in sales relative to the same quarter in the following year. The red dashed line connects estimated coefficients, β_τ, of the following regression performed in the supplier sample:

$$\Delta Sales_{i,t,t+4} = \alpha + \sum_{\tau=-7}^{3} \beta_\tau . HitsFirm_{i,t-\tau} + \eta_i + \pi_t + \epsilon_{i,t}$$

The blue solid line connects estimated coefficients, γ_τ, of the following regression performed in the customer sample:

$$\Delta Sales_{i,t,t+4} = \alpha + \sum_{\tau=-7}^{3} \beta_\tau . HitsFirm_{i,t-\tau} + \sum_{\tau=-7}^{3} \gamma_\tau . HitsSupplier_{i,t-\tau} + \eta_i + \pi_t + \epsilon_{i,t},$$

where π_t and η_i are year-quarter and firm fixed effects respectively, $HitsFirm_{i,t-\tau}$ is a dummy equal to one if a natural disaster hits firm i in year-quarter $t-\tau$, and $HitsSupplier_{i,t-\tau}$ is a dummy equal to one if a natural disaster hits at least one supplier of firm i in year-quarter $t-\tau$. Standard errors are clustered at the firm level in both regressions. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively. The sample period spans 1978 to 2010.

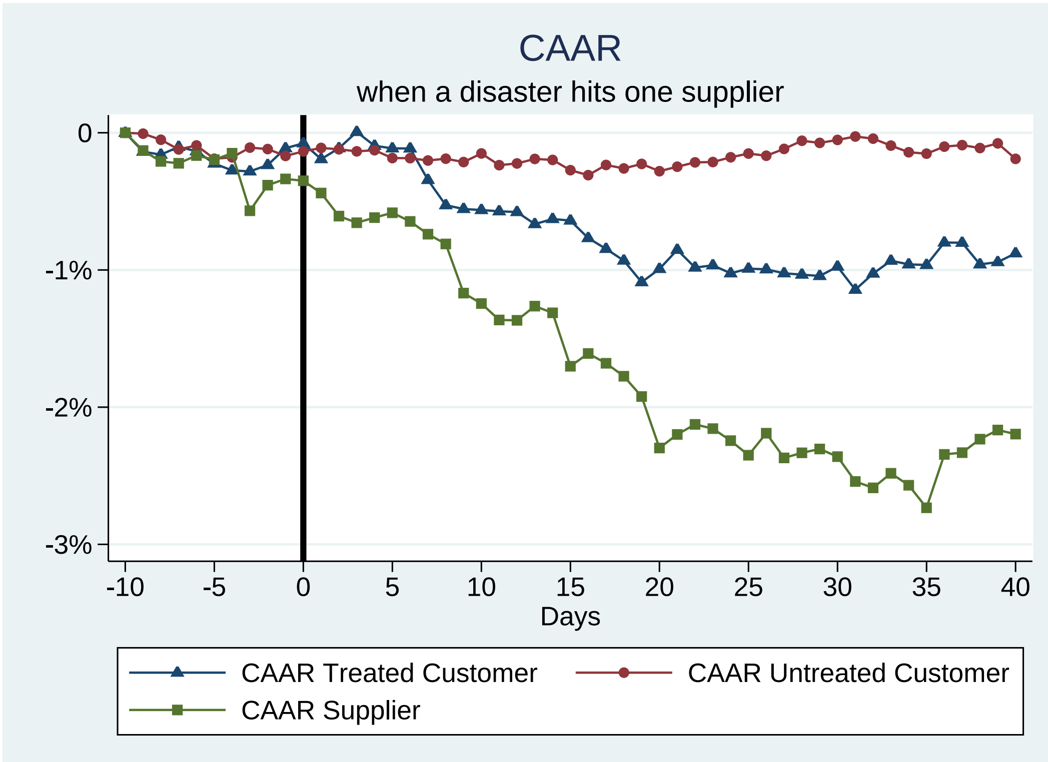

Figure 5. Cumulative Average Abnormal Returns. This figure presents cumulative average abnormal returns (CAAR) of customer firms around the first day of a natural disaster affecting (at least) one of its suppliers. When more than one supplier is affected by the same natural disaster, the event day is the earliest date across affected suppliers reported in SHELDUS database. Abnormal returns are computed after estimating, for each firm-disaster pair, a 4-factor Fama-French-Carhart model over the interval from 260 to 11 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, for which the firm itself is hit by the disaster, or for which the firm or one of its suppliers are hit by another major disaster in the previous or following 30 trading days on either side of the event date are excluded. We find 1,039 customer firm-disaster pairs satisfying these requirements.

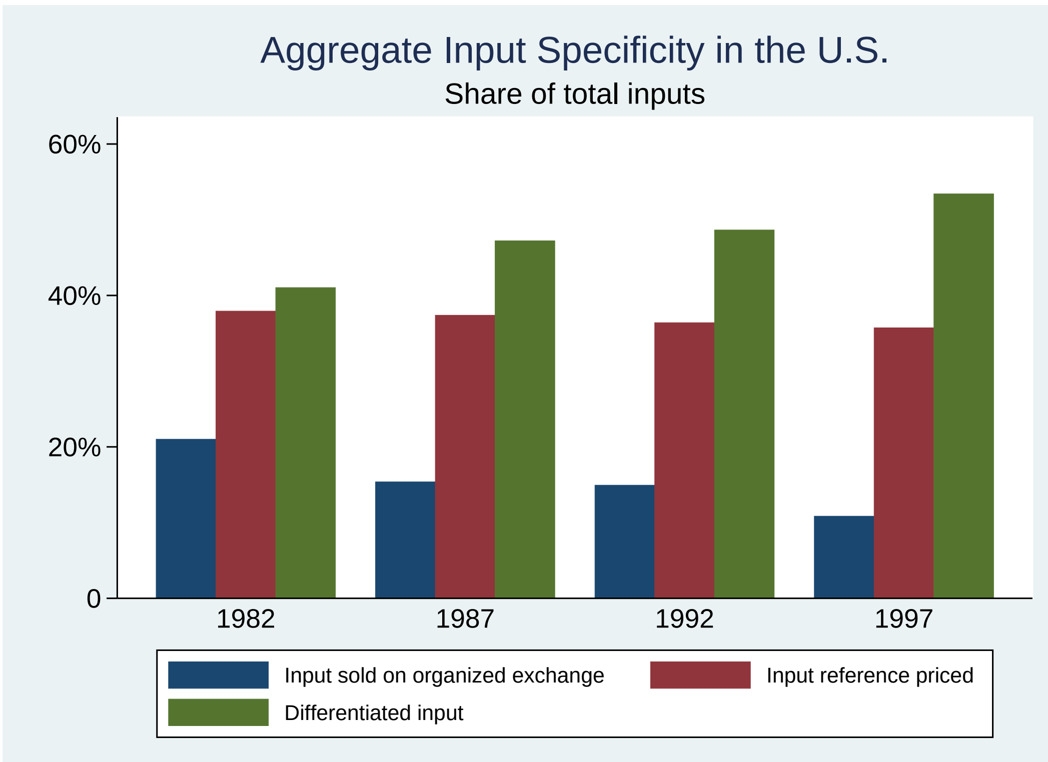

Figure 6. Aggregate Input Specificity in the U.S. This figure is based on the computation of Nunn (2007). The author uses the U.S. Input-Output Use Table to identify which intermediate inputs are used and in what proportions, in the production of each final good. Then, using data from Rauch (1999), inputs are sorted into those sold on an organized exchange, those which are referenced priced in a trade publication, and those that are differentiated.

Table 1. List of Major Disasters

This table describes the 35 natural disasters included in the sample. Names, dates, number of affected counties, and the location of each natural disaster are obtained from the SHELDUS database at the University of South Carolina. The list is restricted to events classified as *Major Disasters* in SHELDUS, with total direct estimated damages above one billion 2013 constant dollars and lasting less than 30 days. The share of total U.S. employment affected by each natural disaster is computed from County Business Pattern data publicly provided by the U.S. Census Bureau. Abbreviations for U.S. states presented in column 4 are: AL (Alabama), AK (Alaska), AZ (Arizona), AR (Arkansas), CA (California), CO (Colorado), CT (Connecticut), DE (Delaware), FL (Florida), GA (Georgia), HI (Hawaii), ID (Idaho), IL (Illinois), IN (Indiana), IA (Iowa), KS (Kansas), KY (Kentucky), LA (Louisiana), ME (Maine), MD (Maryland), MA (Massachusetts), MI (Michigan), MN (Minnesota), MS (Mississippi), MO (Missouri), MT (Montana), NE (Nebraska), NV (Nevada), NH (New Hampshire), NJ (New Jersey), NM (New Mexico), NY (New York), NC (North Carolina), ND (North Dakota), OH (Ohio), OK (Oklahoma), OR (Oregon), PA (Pennsylvania), RI (Rhode Island), SC (South Carolina), SD (South Dakota), TN (Tennessee), TX (Texas), UT (Utah), VT (Vermont), VA (Virginia), WA (Washington), WV (West Virginia), WI (Wisconsin), WY (Wyoming). The sample period is from January 1978 to December 2010.

Disaster	Date	# Counties	U.S. employment affected (%)	Location
Helen Eruption	May 1980	2	0.03	WA
Alicia	August 1983	139	4.72	TX
Elena	August 1985	32	0.54	AL, FL, LA, MS
Juan	October 1985	66	3.58	AL, FL, LA, MS, TX
Hugo	September 1989	71	1.43	NC, SC, VA
Loma Earthquake	October 1989	8	2.56	CA
Bob	August 1991	54	7.06	MA, ME, NC, NH, NY, RI
Oakfland Hills Firestorm	October 1991	1	0.54	CA
Andrew	August 1992	51	2.67	AL, FL, LA, MS
Iniki	September 1992	1	0.02	HI
Blizzard	March 1993	221	11.15	AL, CT, FL, GA, MA, MD, NJ, OH, SC, VA, VT
Northridge Earthquake	January 1994	1	3.69	CA
Alberto	July 1994	41	0.66	AL, FL, GA
Severe Storms	May 1995	105	5.21	LA, MS, OK, TX
Opal	October 1995	186	6.43	AL, FL, GA, LA, MS, NC, SC
Blizzard	January 1996	319	14.50	CT, DE, IN, KY, MA, MD, NC, NJ, NY, PA, VA, WV
Fran	September 1996	100	2.02	NC, SC, VA, WV
Ice Storm	January 1998	43	1.09	ME, NH, NY, VT
Bonnie	August 1998	43	1.26	NC, VA
Georges	September 1998	78	3.68	AL, FL, LA, MS
Floyd	September 1999	226	15.70	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Alison	June 2001	77	4.56	AL, FL, GA, LA, MS, PA, TX
Isabel	September 2003	89	4.99	DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV
Southern California Wildfires	October 2003	3	1.78	CA
Charley	August 2004	67	3.94	FL, GA, NC, SC
Frances	September 2004	133	4.61	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Ivan	September 2004	135	5.82	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Jeanne	September 2004	216	6.06	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
Dennis	July 2005	200	5.38	AL, FL, GA, MS, NC
Katrina	August 2005	288	9.21	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
Rita	September 2005	123	3.75	AL, AR, FL, LA, MS
Wilma	October 2005	24	3.55	FL
Midwest Floods	June 2008	216	5.25	IA, IL, IN, MN, MO, NE, WI
Gustav	September 2008	38	0.66	AL, AR, LA, MS
Ike	September 2008	161	5.44	AR, IL, IN, KY, LA, MI, MO, MS, OH, PA, TN, TX

Table 2. Descriptive Statistics

This table presents the summary statistics for our sample. Panel A presents the customer sample, which consists of 60,682 firm-quarters between 1978 and 2010. There are 2,014 firms in this sample. A firm is included in the sample for each quarter between the first and last year it appears as a customer in the Compustat Segment files. The main variables of interest are the growth in sales and cost of goods sold relative to the same quarter in the following year. Panel A also reports for customer firms the average duration of relationships with their suppliers (computed as the number of years between the first and last year the supplier reports the firm as a customer in the Compustat Segment files), the average distance in miles (computed using the Haversine formula) between the headquarters (HQs) county of the firm and the headquarters county of its suppliers, and the average suppliers' input share (measured as the ratio of the suppliers' sales of the supplier to the firm over the firm's cost of goods sold) separately for relationships with specific (S) and non-specific (NS) suppliers. In columns (1) and (2), a firm is considered as specific if it belongs to a 2-digit SIC codes industry producing differentiated goods as defined in Giannetti et al. (2011) (this sectoral classification is itself based on the Rauch (1999) product classification). In columns (3) and (4), a firm is considered specific if its ratio of R&D expenses over sales is above the median in the two years prior to any given quarter. In columns (5) and (6), a firm is considered as specific if the number of patents it issued in the past five years is above the median. The last part of Panel A compares the size, age and return on assets (ROA) of eventually treated firms – that is, having at least once in the sample period one supplier hit by a major natural disaster – and never treated firms. Panel B presents the supplier sample, which consists of 92,977 firm-quarters between 1978 and 2010. There are 4,112 firms in this sample. A firm is included in the sample for each quarter between the first and last year it reports another firm as a customer in the Compustat Segment files. The main variable of interest is the growth in sales relative to the same quarter in the following year.

Panel A:	Customer Sample					
	Obs.	Mean	Std. Dev.	p1	p50	p99
Sales growth (t,t+4)	60682	0.091	0.346	-0.610	0.039	1.784
Cogs growth (t,t+4)	59676	0.096	0.383	-0.641	0.037	2.001
Disaster hits firm (t)	60682	0.014	0.117	0.000	0.000	1.000
Disaster hits one supplier (t)	60682	0.019	0.135	0.000	0.000	1.000
Number of suppliers	60682	1.986	4.844	0.000	1.000	23.000
	DIFF.		R&D		PATENT	
	S	NS	S	NS	S	NS
Av. duration of relationships	7.272	5.974	7.170	6.068	8.054	5.907
Av. supplier-customer HQs distance	1163	1083	1236	1038	1206	1088
Av. suppliers' input share	0.015	0.023	0.017	0.022	0.021	0.019
	Eventually Treated			Never Treated		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Assets	29303	9052	10477	31379	3273	5733
Age	29303	28.590	15.784	31379	19.575	15.601
ROA	29303	0.148	0.083	31379	0.116	0.123

Panel B:	Supplier Sample					
	Obs.	Mean	Std. Dev.	p1	p50	p99
Sales growth (t,t+4)	92977	0.158	0.698	-0.887	0.039	4.066
Disaster hits firm (t)	92977	0.015	0.120	0.000	0.000	1.000
Disaster hits a customer (t)	92977	0.012	0.107	0.000	0.000	1.000
Disaster hits a customer's supplier (t)	92977	0.071	0.256	0.000	0.000	1.000
Number of customers	92977	1.223	0.981	0.000	1.000	4.000
% Employees at HQs' county	67322	0.576	0.371	0.000	0.618	1.000

Table 3. Natural Disasters Disruptions – Supplier Sales Growth

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on a dummy indicated whether the firm is hit by a major disaster in each of the previous three quarters, the current quarter, and each of the following four quarters. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our supplier sample (described in Table 2, Panel B) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$			
Disaster hits firm (t+4)	0.005	0.003	0.006	0.003
	(0.020)	(0.020)	(0.019)	(0.022)
Disaster hits firm (t+3)	-0.054***	-0.054***	-0.048***	-0.047**
	(0.017)	(0.018)	(0.018)	(0.020)
Disaster hits firm (t+2)	-0.038*	-0.036*	-0.015	-0.027
	(0.021)	(0.021)	(0.021)	(0.025)
Disaster hits firm (t+1)	-0.036*	-0.037*	-0.021	-0.031
	(0.020)	(0.020)	(0.020)	(0.025)
Disaster hits firm (t)	-0.029	-0.028	-0.010	-0.023
	(0.022)	(0.022)	(0.022)	(0.026)
Disaster hits firm (t-1)	0.000	0.002	0.014	-0.009
	(0.023)	(0.023)	(0.023)	(0.026)
Disaster hits firm (t-2)	0.002	-0.001	0.001	0.006
	(0.023)	(0.023)	(0.023)	(0.027)
Disaster hits firm (t-3)	-0.004	-0.006	-0.011	0.002
	(0.021)	(0.021)	(0.020)	(0.022)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	92977	92977	92977	92977
R^2	0.193	0.208	0.238	0.234

Table 4. Natural Disasters Disruptions – Specific vs. Non-specific Suppliers

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on a dummy indicating whether the firm is hit by a major disaster in the current or following three quarters, a dummy taking the value of one if the firm which is hit is a specific one, as well as fiscal-quarter, year-quarter, and firm fixed effects. In columns (1) and (2), a firm is considered as specific if it belongs to a 2-digit SIC codes industry producing differentiated goods as defined in Giannetti et al. (2011). In columns (3) and (4), a firm is considered specific if the ratio of its R&D expenses over sales is above the median in the two years prior to any given quarter. In columns (5) and (6), a firm is considered as specific if the number of patents it issued in the previous five years is above the median. All specifications control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our supplier sample (described in Table 2, Panel B) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$					
Supplier specificity:	DIFF.		R&D		PATENT	
Disaster hits firm (t,t+3)	-0.051***	-0.048**	-0.060***	-0.055***	-0.054***	-0.049***
	(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
Disaster hits specific firm (t,t+3)	0.032	0.027	0.047*	0.038	0.040	0.030
	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)
High R&D firm			-0.037	-0.031		
			(0.024)	(0.024)		
High PATENT firm					-0.088***	-0.043***
					(0.016)	(0.016)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	No	Yes	No	Yes
Observations	92977	92977	92977	92977	92977	92977
R^2	0.193	0.208	0.193	0.208	0.193	0.208

Table 5. Downstream Propagation – Baseline

This table presents estimated coefficients from panel regressions of firms' sales growth (Panel A) or cost of goods sold growth (Panel B) relative to the same quarter in the following year on a dummy indicating whether (at least) one dependent supplier has been hit by a major disaster in the current quarter. All regressions include one dummy indicating whether the firm itself has been hit by a major disaster in the current quarter, as well as fiscal-quarter, year-quarter, and firm fixed effects. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

Panel A:	Sales Growth $(t, t+4)$			
Disaster hits one supplier (t)	-0.029***	-0.023***	-0.020**	-0.019**
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits firm (t)	-0.023**	-0.018	-0.010	-0.009
	(0.012)	(0.012)	(0.011)	(0.011)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60682	60682	60682	60682
R^2	0.256	0.287	0.343	0.337

Panel B:	Cost of Goods Sold Growth $(t, t+4)$			
Disaster hits one supplier (t)	-0.027***	-0.021**	-0.020**	-0.019**
	(0.010)	(0.010)	(0.009)	(0.009)
Disaster hits firm (t)	-0.016	-0.012	-0.010	-0.009
	(0.013)	(0.014)	(0.011)	(0.011)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	59676	59676	59676	59676
R^2	0.208	0.237	0.343	0.337

Table 6. Downstream Propagation – Sales Growth Dynamics

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on dummies indicating whether (at least) one dependent supplier is hit by a major disaster in each of the previous three quarters, the current quarter, and each of the following four quarters. All regressions include dummies indicating whether the firm itself is hit by a major disaster in each of the previous three quarters, the current quarter, and each of the following four quarters, as well as fiscal-quarter, year-quarter and firm fixed effects. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$			
Disaster hits one supplier (t+4)	0.004	0.011	0.014	0.013
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t+3)	-0.006	-0.003	0.002	0.000
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t+2)	-0.007	-0.001	0.007	0.004
	(0.010)	(0.010)	(0.010)	(0.010)
Disaster hits one supplier (t+1)	-0.019**	-0.014	-0.010	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t)	-0.029***	-0.024***	-0.021**	-0.020**
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t-1)	-0.016*	-0.011	-0.012	-0.010
	(0.010)	(0.010)	(0.010)	(0.010)
Disaster hits one supplier (t-2)	-0.016*	-0.011	-0.010	-0.007
	(0.009)	(0.009)	(0.009)	(0.010)
Disaster hits one supplier (t-3)	-0.001	0.002	0.002	0.010
	(0.011)	(0.011)	(0.011)	(0.011)
Disaster hits firm (t+4)	-0.004	-0.003	-0.002	-0.002
	(0.014)	(0.014)	(0.014)	(0.014)
Disaster hits firm (t+3)	-0.014	-0.014	-0.013	-0.012
	(0.012)	(0.012)	(0.012)	(0.013)
Disaster hits firm (t+2)	-0.036***	-0.031**	-0.017	-0.010
	(0.012)	(0.012)	(0.012)	(0.015)
Disaster hits firm (t+1)	-0.035***	-0.030**	-0.020*	-0.021
	(0.012)	(0.012)	(0.012)	(0.015)
Disaster hits firm (t)	-0.026**	-0.021	-0.013	-0.015
	(0.013)	(0.013)	(0.013)	(0.016)
Disaster hits firm (t-1)	-0.019	-0.016	-0.010	-0.009
	(0.013)	(0.013)	(0.012)	(0.015)
Disaster hits firm (t-2)	0.001	0.003	-0.001	-0.006
	(0.012)	(0.012)	(0.012)	(0.014)
Disaster hits firm (t-3)	0.014	0.013	0.008	0.011
	(0.011)	(0.011)	(0.011)	(0.012)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60682	60682	60682	60682
R^2	0.256	0.288	0.343	0.337

Table 7. Test of Parallel Trends

This table reports the results of F-tests for the joint significance of fixed effects in regressions of firms' sales growth in our customer sample. All specifications include year-quarter fixed effects, fiscal-quarter fixed effects, firm fixed effects, the full set of year-quarter fixed effects interacted with a dummy which equals one for eventually treated firms and cluster standard errors at the firm level. Rows (2) to (5) also include the full set of year-quarter fixed effects interacted with terciles of firm size. Rows (3) and (5) also include the full set of year-quarter fixed effects interacted with terciles of firm age. Rows (4) and (5) also include the full set of year-quarter fixed effects interacted with terciles of firm return on assets. Each cell reports for groups of fixed effects the value of the F-statistic and, in parentheses, the p-value, and number of constraints. The sample period is from 1978 to 2010.

Customer sample	F-tests on fixed effects for Year Quarter×__					
	Size	Age	ROA	Eventually Treated	N	Adj R^2
Sales Growth				0.90 (0.6805, 57)	20631	0.28
Sales Growth	2.18 (<0.0001, 116)			0.88 (0.7182, 57)	20631	0.28
Sales Growth	1.95 (<0.0001, 116)	1.70 (<0.0001, 99)		0.89 (0.7147, 57)	20631	0.28
Sales Growth	2.10 (<0.0001, 116)		1.08 (0.2812, 116)	0.91 (0.6557, 57)	20631	0.28
Sales Growth	1.84 (<0.0001, 116)	1.77 (<0.0001, 99)	1.08 (0.2754, 116)	0.91 (0.2918, 57)	20631	0.28

Table 8. Downstream Propagation – Robustness

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on a dummy indicating whether (at least) one dependent supplier has been hit by a major disaster in the current quarter. All regressions include one dummy indicating whether the firm itself has been hit by a major disaster in the current quarter, as well as fiscal-quarter, year-quarter and firm fixed effects. Panel A also includes a dummy indicating whether 10% or more of the firm's workforce is hit. Panel B includes a dummy indicating whether (at least) one location of any supplier once in a relationship with the firm is hit. Columns (2) to (4) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Column (3) also includes 48 Fama-French industry dummies interacted with year dummies. Column (4) also includes state dummies interacted with year dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

Panel A:	Sales Growth $(t, t+4)$			
Disaster hits more than 10% of firm's workforce (t)	-0.011	-0.007	0.006	-0.004
	(0.011)	(0.011)	(0.011)	(0.011)
Disaster hits one supplier (t)	-0.028***	-0.022**	-0.020**	-0.019**
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits firm (t)	-0.015	-0.013	-0.014	-0.006
	(0.014)	(0.014)	(0.014)	(0.013)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60682	60682	60682	60682
R^2	0.256	0.287	0.343	0.337

Panel B:	Sales Growth $(t, t+4)$			
Disaster hits *any eventually linked suppliers*' location (t)	0.005	0.008	0.010	0.007
	(0.008)	(0.008)	(0.008)	(0.007)
Disaster hits one supplier (t)	-0.032***	-0.028***	-0.026***	-0.023**
	(0.011)	(0.010)	(0.010)	(0.010)
Disaster hits firm (t)	-0.023**	-0.018	-0.010	-0.009
	(0.012)	(0.012)	(0.011)	(0.011)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Industry Year FE	No	No	Yes	No
State Year FE	No	No	No	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	Yes	Yes
Observations	60682	60682	60682	60682
R^2	0.256	0.287	0.343	0.337

Table 9. Downstream Propagation – Input Specificity

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on on two dummies indicating whether (at least) one specific supplier and whether (at least) one non-specific supplier is hit by a major disaster in the current quarter. In columns (1) and (2), a supplier is considered as specific if it belongs to a 2-digit SIC codes industry producing differentiated goods as defined in Giannetti et al. (2011). In columns (3) and (4), a supplier is considered specific if its ratio of R&D expenses over sales is above the median in the two years prior to any given quarter. In columns (5) and (6), a supplier is considered as specific if the number of patents it issued in the previous five years is above the median. All regressions include one dummy indicating whether the firm itself has been hit by a major disaster in the current quarter, as well as fiscal-quarter, year-quarter, and firm fixed effects. Columns (2), (4) and (6) also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our customer sample (described in Table 2, Panel A) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$					
Supplier specificity:	DIFF.		R&D		PATENT	
Disaster hits one non-specific supplier (t)	-0.017	-0.014	-0.014	-0.011	-0.018*	-0.013
	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)
Disaster hits one specific supplier (t)	-0.039***	-0.029**	-0.036***	-0.026**	-0.038***	-0.034***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Disaster hits firm (t)	-0.023**	-0.018	-0.023**	-0.018	-0.023**	-0.018
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	No	Yes	No	Yes	No	Yes
Observations	60682	60682	60682	60682	60682	60682
R^2	0.256	0.287	0.256	0.287	0.256	0.287

Table 10. Downstream Propagation – Effect on Firm Value

This table presents CAAR of customer firms around the first day of a natural disaster affecting (at least) one of its suppliers. When more than one supplier is affected by the same natural disaster, the event day is the earliest date across affected suppliers reported in SHELDUS database. Abnormal returns are computed after estimating, for each firm-disaster pair, a 4-factor Fama-French-Carhart model over the interval from 260 to 11 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, for which the firm itself is hit by the disaster, or for which the firm or one of its suppliers are hit by another major disaster in the previous or following 30 trading days on either side of the event date are excluded. ADJ-BMP t-statistics, presented in parentheses, are computed with the standardized cross-sectional method of Boehmer et al. (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010). Column (2) reports CAAR of directly hit supplier firms. Column (3) reports CAAR of unaffected customer firms, that is including firm-disaster pairs for which no suppliers reporting the firm as a customer have been hit by the disaster. Computations of abnormal returns follow the same procedure as above. The sample period is from 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	CAAR		
	Customers (N=1039)	Suppliers (Direct effect) (N=1530)	Customers (Control group) (N=6081)
$[-10,-1]$	-0.113	-0.336	-0.169**
	(0.108)	(-1.033)	(-2.304)
$[0,10]$	-0.451***	-0.908***	0.018
	(-3.087)	(-2.693)	(0.320)
$[11,20]$	-0.429**	-1.053***	-0.129
	(-2.528)	(-2.981)	(-0.594)
$[21,30]$	0.017	-0.063	0.228
	(0.812)	(-0.364)	(1.496)
$[-10,30]$	-0.975**	-2.360***	-0.052
	(-2.320)	(-3.536)	(-0.463)

Table 11. Downstream Propagation – Input Specificity and Effect on Firm Value

This table presents CAAR of customer firms separately for events affecting (at least one) specific supplier or only non-specific suppliers. In column (1), a supplier is considered as specific if it belongs to a 2-digit SIC codes industry producing differentiated goods as defined in Giannetti et al. (2011). In column (3), a supplier is considered specific if the ratio of its R&D expenses over sales is above the median in the two years prior to any given quarter. In column (5), a supplier is considered as specific if the number of patents it issued in the previous five years is above the median. Abnormal returns are computed after estimating, for each firm-disaster pair, a 4-factor Fama-French-Carhart model over the interval from 260 to 11 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, for which the firm itself is hit by the disaster, or for which the firm or one of its suppliers are hit by another major disaster in the previous or following 30 trading days on either side of the event date are excluded. ADJ-BMP t-statistics, presented in parentheses, are computed with the standardized cross-sectional method of Boehmer et al. (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010).

	Customers' CAAR when disaster hits at least one supplier					
Supplier specificity:	DIFF.		R&D		PATENT	
	N=473	N=566	N=497	N=542	N=362	N=677
At least one specific supplier?	Yes	No	Yes	No	Yes	No
$[-10, -1]$	-0.615	0.307	-0.067	-0.155	0.012	-0.179
	(-1.065)	(1.167)	(-0.070)	(0.204)	(0.252)	(-0.063)
$[0, 10]$	-0.303	-0.574***	-0.791***	-0.139	-1.073***	-0.117
	(-1.128)	(-2.874)	(-2.905)	(-1.304)	(-2.925)	(-1.476)
$[11, 20]$	-0.545	-0.332*	-0.352	-0.500**	-0.406	-0.442**
	(-1.393)	(-1.888)	(-1.171)	(-2.188)	(-1.005)	(-2.341)
$[21, 30]$	-0.147	0.154	-0.101	0.125	-0.780	0.443**
	(0.089)	(0.879)	(-0.060)	(1.044)	(-1.512)	(1.995)
$[-10, 30]$	-1.610*	-0.445	-1.310**	-0.669	-2.247**	-0.296
	(-1.752)	(-1.318)	(-2.003)	(-1.142)	(-2.560)	(-0.835)

Table 12. Stock Returns and Future Sales Growth

Panel A of this table presents estimated coefficients from regressions of customer firms' sales growth (columns (1) and (2)) or customer firms' sales growth residuals (columns (3) and (4)) relative to the same quarter in the following year on CAR of customer firms around the first day of a natural disaster affecting (at least) one of their suppliers. All regressions include year-quarter fixed effects. Sales growth residuals are residuals of a regression of sales growth on fiscal-quarter, year-quarter and firm fixed effects, as well controls for size, age, and return on assets interacted with year-quarter dummies. Abnormal returns are computed after estimating, for each firm-disaster pair, a 4-factor Fama-French-Carhart model over the interval from 260 to 11 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, for which the firm itself is hit by the disaster, or for which the firm or one of its suppliers are hit by another major disaster in the previous or following 30 trading days on either side of the event date are excluded. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

Panel A:	Treated Customers			
	Sales Growth $(t, t+4)$		Sales Growth Res. $(t, t+4)$	
$\text{CAR}[-10, 20]$	0.194**		0.140*	
	(0.080)		(0.072)	
$\text{CAR}[-10, -1]$		0.017		-0.140
		(0.149)		(0.134)
$\text{CAR}[0, 20]$		0.250***		0.252***
		(0.093)		(0.084)
Year Quarter FE	Yes	Yes	Yes	Yes
Observations	769	769	763	763
R^2	0.129	0.130	0.060	0.068

Panel B:	Placebo: Untreated Customers			
	Sales Growth $(t, t+4)$		Sales Growth Res. $(t, t+4)$	
$\text{CAR}[-10, 20]$	-0.010		-0.024	
	(0.044)		(0.036)	
$\text{CAR}[-10, -1]$		-0.052		-0.046
		(0.082)		(0.067)
$\text{CAR}[0, 20]$		0.028		-0.023
		(0.050)		(0.040)
Year Quarter FE	Yes	Yes	Yes	Yes
Observations	4192	4192	4138	4138
R^2	0.054	0.055	0.009	0.009

Table 13. Horizontal Propagation – Related Suppliers' Sales Growth

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on one dummy indicating whether one of the firm customer's other suppliers is hit by a major disaster in the current or previous three quarters. Columns (2) to (4) split customer's other suppliers into specific and non-specific suppliers. All regressions include fiscal-quarter, year-quarter, firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter and firm fixed effects. All regressions include two dummies indicating whether the firm itself is hit in the current or following three quarters, and whether the firm is hit in the previous three quarters, as well as one dummy indicating whether one of the firm's customer is hit in the current or previous three quarters. Standard errors presented in parentheses are clustered at the firm-level. Regressions contain all firm-quarters of our supplier sample (described in Table 2, Panel B) between 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Sales Growth $(t, t+4)$			
Supplier specificity:		DIFF.	R&D	PATENT
Disaster hits one customer's supplier (t-3,t)	-0.032***			
	(0.011)			
Disaster hits one customer's specific supplier (t-3,t)		-0.033***	-0.032***	-0.036***
		(0.011)	(0.012)	(0.012)
Disaster hits one customer's non-specific supplier (t-3,t)		-0.019	-0.012	-0.017
		(0.012)	(0.011)	(0.012)
Disaster hits one customer (t-3,t)	-0.005	-0.004	-0.004	-0.003
	(0.019)	(0.019)	(0.019)	(0.019)
Disaster hits firm (t,t+3)	-0.041***	-0.041***	-0.041***	-0.041***
	(0.015)	(0.015)	(0.015)	(0.015)
Disaster hits firm (t-3,t-1)	-0.007	-0.008	-0.008	-0.008
	(0.017)	(0.017)	(0.017)	(0.017)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	Yes	Yes	Yes	Yes
Observations	92977	92977	92977	92977
R^2	0.208	0.208	0.208	0.208

Table 14. Horizontal Propagation – Robustness

This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the following year on one dummy indicating whether one of the other suppliers to a customer of the firm is hit by a major disaster in the current or previous three quarters, as well as in Panel A a dummy indicating whether 10% or more of the firm's workforce is hit by a major disaster in the current or previous three quarters, in Panel B a dummy indicating whether (at least) one location of any other suppliers once in a relationship with a customer of the firm is hit by a major disaster in the current or previous three quarters, in Panel C a dummy indicating whether (at least) one other supplier of any customer once in a relationship with the firm is hit by a major disaster in the current or previous three quarters. Columns (2) to (4) split the customers' other suppliers into specific and non-specific suppliers. All regressions include fiscal-quarter, year-quarter, firm-level characteristics (dummies indicating terciles of size, age and ROA respectively) interacted with year-quarter and firm fixed effects. Standard errors presented in parentheses are clustered at the firm level. The sample period is from 1978 to 2010. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

	Supplier's Sales Growth $(t, t+4)$			
Panel A:		DIFF.	R&D	PATENT
Disaster hits at least 10% of firm's workforce (t-3,t)	0.008	0.008	0.008	0.008
	(0.017)	(0.017)	(0.017)	(0.017)
	(0.022)	(0.022)	(0.022)	(0.022)
Disaster hits one customer's supplier (t,t+3)	-0.032***			
	(0.011)			
Disaster hits one customer's specific supplier (t,t+3)		-0.033***	-0.032***	-0.036***
		(0.011)	(0.012)	(0.012)
Disaster hits one customer's non-specific supplier (t,t+3)		-0.019	-0.012	-0.017
	(0.012)	(0.011)	(0.012)	
Disaster hits one customer (t,t+3)	-0.005	-0.004	-0.004	-0.003
	(0.019)	(0.019)	(0.019)	(0.019)
Disaster hits firm (t,t+3)	-0.041***	-0.041***	-0.041***	-0.041***
	(0.015)	(0.015)	(0.015)	(0.015)
Disaster hits firm (t-3,t-1)	-0.014	-0.014	-0.014	-0.014
Panel B:		DIFF.	R&D	PATENT
Disaster hits *any customers' eventually linked* supplier (t-3,t)	-0.004	-0.003	-0.003	-0.003
	(0.017)	(0.017)	(0.017)	(0.017)
Disaster hits one customer's supplier (t,t+3)	-0.032***			
	(0.011)			
Disaster hits one customer's specific supplier (t,t+3)		-0.033***	-0.032***	-0.036***
		(0.011)	(0.012)	(0.012)
Disaster hits one customer's non-specific supplier (t,t+3)		-0.019	-0.012	-0.017
		(0.012)	(0.011)	(0.012)
Disaster hits one customer (t,t+3)	-0.005	-0.004	-0.004	-0.003
	(0.019)	(0.019)	(0.019)	(0.019)
Disaster hits firm (t,t+3)	-0.041***	-0.041***	-0.041***	-0.041***
	(0.015)	(0.015)	(0.015)	(0.015)
Disaster hits firm (t-3,t-1)	-0.007	-0.008	-0.008	-0.008
	(0.017)	(0.017)	(0.017)	(0.017)

Table 14. (continued)

Panel C:		DIFF.	R&D	PATENT
Disaster hits *any eventually linked customer's* supplier (t-3,t)	0.000	0.002	-0.003	0.002
	(0.016)	(0.014)	(0.014)	(0.014)
Disaster hits one customer's supplier (t,t+3)	-0.032**			
	(0.016)			
Disaster hits one customer's specific supplier (t,t+3)		-0.034***	-0.031**	-0.036***
		(0.013)	(0.013)	(0.013)
Disaster hits one customer's non-specific supplier (t,t+3)		-0.020	-0.011	-0.019
		(0.013)	(0.013)	(0.014)
Disaster hits one customer (t,t+3)	-0.005	-0.004	-0.004	-0.003
	(0.019)	(0.019)	(0.019)	(0.019)
Disaster hits firm (t,t+3)	-0.041***	-0.041***	-0.041***	-0.041***
	(0.015)	(0.015)	(0.015)	(0.015)
Disaster hits firm (t-3,t-1)	-0.007	-0.008	-0.007	-0.008
	(0.018)	(0.017)	(0.017)	(0.017)
Firm FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year Quarter FE	Yes	Yes	Yes	Yes
Observations	92977	92977	92977	92977
R^2	0.208	0.208	0.208	0.208