INPUT SPECIFICITY AND THE PROPAGATION OF IDIOSYNCRATIC SHOCKS IN PRODUCTION NETWORKS*

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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. *JEL* Codes: L14, E23, E32.

I. 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

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may help explain the aggregation of sector-specific shocks and have found mixed empirical evidence of the importance of such linkages. Relative to the measurement of spillovers across sectors, spillovers within networks of firms have received little attention in the empirical 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 should be flexible enough to recompose their production mix, or to switch to other suppliers. The gradual decrease in trade tariffs and transportation costs, and 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.

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 by 2 to 3 percentage points in sales growth following the event.

[1] Natural disasters have already been used in prior work to instrument for school displacement (Imberman, Kugler and Sacerdote, 2012), positive local demand shocks Bernile, Korniotis and Kumar, 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).

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. In robustness tests, we show that the estimates are similar when we control for heterogeneous trends across firms with many or few suppliers, when we weight regression by size, when we restrict the sample to eventually treated firms only, and whether or not we include local supplier-customer relationships in the sample. Given that we are interested in the propagation of firm-specific shocks, we also check that we are not picking up sector-level or even macroeconomic shocks. Instead, we find that the effect is not driven by events that affect many suppliers at the same time, or a large share of the same industry.

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.

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. 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. We find that the propagation of input shocks varies strongly with our measures of specificity. Firms' sales growth and stock prices significantly 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.

A potential concern with our analysis is the selected nature of our network structure. We obtain firms' network relationships from the obligation that publicly listed U.S. firms have under regulation Statement of Financial Accounting Standards (SFAS) No. 131 to report selected information about operating segments in interim financial reports issued to shareholders, including the identity of any customer representing more than 10% of total reported sales. Hence, our sample comprises only suppliers with major customers, and only publicly listed firms, which might bias our estimates. To ensure that our results are not driven by this selection issue, we run similar analysis using an alternative network structure and confirm that our results are not sensitive to the restriction of the sample to publicly listed firms.

To check whether our estimates fall within a reasonable range, we present a general equilibrium network model based on Long and Plosser (1983) and Acemoglu et al. (2012), and find that our reduced-form estimates are consistent with the model predictions for high levels of complementarity across intermediate input suppliers. We finally assess the economic importance of the propagation channel by computing the aggregate dollar value of sales lost for suppliers and customers in our sample, after suppliers are hit by natural disasters. We find that \$1 of lost sales at the supplier level leads to \$2.4 of lost sales at the customer level, which indicates that relationships in production networks substantially amplify idiosyncratic shocks.

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.[2] They also highlight the presence of strong interdependencies in production networks, which are highly relevant in order to assess the implications of corporate bailouts.[3]

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 La'O, 2013; Caliendo et al., 2014; Baqaee, 2015). 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, Sarte and Watson, 2011), and the specification of the production function (Jones, 2011; Atalay, 2013). While earlier work has focused on the

[2]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).

[3]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."

linkages across sectors,[4] we carefully estimate linkages within networks of firms.[5] In contemporaneous work, Todo, Nakajimi amd Matous (2014), Carvalho, Nirei and Saito (2014) and Boehm, Flaaen and Pandalai-Nayar (2015) 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.[6]

Furthermore, we build on earlier work that considers the importance of switching costs 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, Sushka and Polonchek, 1993; Hubbard, Kuttner and Palia, 2002; Khwaja and Mian, 2008; Fernand, May and Megginson, 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 (Antràs, Fort and Tintelnot, 2014; Bernard, Moxnes and Saito, 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

[4] Di Giovanni, Levchenko and Mejean (2014) is a recent exception.

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

[6] The finding that shocks propagate horizontally is related to Kee (2015), who documents that domestic firms can benefit from the entry of foreign rivals through the enhanced productivity of their shared domestic suppliers.

and Ivanov, 2012; Kelly, Lustig and Van Nieuwerburgh, 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, Dasgupta and Kim, 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. Section II presents our empirical strategy. Section III presents the data. Section IV describes the results, and Section V concludes.

II. 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 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,[7] we find that in our sample of suppliers, the average (median) firm has 60% (67%) of its employees located at its headquarters (see Table II).

There are many different but unobservable reasons why disasters might affect firms' output. It might be that they trigger power outages disrupting production.[8] Alternatively,

[7] We describe the data in more detail in Section III.

[8] Hines (2008) find that 44% of major power outages in the U.S. are weather-related (i.e., caused by

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 IV that such disasters have a temporary and significant negative effect on these suppliers' sales growth.[9]

The main focus of the paper is not the disruption to the supplying firm itself but rather the impact on the firm's customers and 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.[10] We consider that S1 is a supplier to C in all years ranging from the first to the last year when 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,[11]

$$(1) \qquad \Delta Sales_{i,t-4,t} = \alpha_0 + \alpha_1.HitsOneSupplier_{i,t-4} + \alpha_2.DisasterHitsFirm_{i,t-4} + \eta_i + \pi_t + \epsilon_{i,t},$$

tornado, hurricane/tropical storm, ice storm, lightning, wind/rain, or other cold weather).

[9] 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.

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

[11] 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 IV, we show that similar results are obtained at the sector level using a quarterly index of industrial output.

where $\Delta Sales_{i,t-4,t}$ is the sales growth between the current quarter and the same quarter in the previous year. $HitsOneSupplier_{i,t-4}$ 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 in the same quarter in the previous year. $DisasterHitsFirm_{i,t-4}$ is a dummy equal to one if the firm is directly hit by a natural disaster in the same quarter in the previous year. η_i and π_t are year-quarter and firm fixed effects. All regressions control for fiscal-quarter fixed effects and for the number of suppliers, with dummies indicating terciles of the number of suppliers three years prior to date t. In some specifications, we include state×year fixed effects and industry×year fixed effects. We also introduce lagged controls for size, age, and profitability interacted with year-quarter fixed effects.[12] We build these controls by interacting year-quarter dummies with terciles of firms' assets, age, and return on assets three 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 check whether we find any effect in the quarter prior to the natural disaster, and we 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 (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 within 300 miles of each other.[13] In addition, we add a dummy in the regression that captures whether the headquarter county location of C is hit by a natural disaster. Finally, we use

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

[13]We show in Table A.7 in the Online Appendix that the estimates are insensitive to this cutoff.

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. To address this concern, we use the unique feature of our data relative to other studies of production networks, namely, that we observe the time series of relationships. By means of illustration, we present in Figure IV the evolution of the supplier-customer network from 1995 to 2000. Relationships that were active in 1995 but not in 2000 are depicted in red. Relationships that are active in both years are depicted in green. Relationships that were not active in 1995 but were active in 2000 are depicted in blue. It is clear from this figure that a substantial share of relationships start or end within this five-year window. This allows us to check whether we only observe an effect of disruptions to S1 on C's output when the 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 IV.E.

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. We thus 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, 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 split the main variable of interest in Equation (1), *Disaster Hits One Supplier*, into two dummy variables, *Disaster hits one specific supplier* and *Disaster hits one non-specific supplier*, indicating respectively whether at least one *specific* and *non-specific* supplier of the firm is hit by a natural disaster.

Finally, we study the effect of the initial shock on S1 on any other supplier S2 of C. To do so, we run an OLS regression in our sample of suppliers, at the firm-quarter level, of sales growth between the current quarter and the same quarter in the previous year on *Disaster hits firm*, a dummy equal to one if the firm is directly hit by a natural disaster; *Disaster hits one customer*, a dummy equal to one if (at least) one customer of the firm is hit by a natural disaster; and *Disaster hits one customer's supplier*, the main variable of interest, 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. In all specifications, we control for fiscal-quarter fixed effects and for the number of customers' suppliers, with dummies indicating terciles of the number of customers' suppliers.[14]

III. Data

III.A. Firm-level information

Financial data and information about firms' headquarter location are retrieved from Compustat North America Fundamentals Quarterly database. We restrict our sample to non-

[14] 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 within 300 miles of either S1 or C. 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.

financial firms whose headquarters are located in the U.S. over the 1978-2013 period.[15] 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.[16] 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.[17] 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.

III.B. 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 particu-

[15]Customer-supplier links detailed below are available only from 1978; 2013 is the last year for which data on major natural disasters are available.

[16]This leads to a non-negligible adjustment. Between 1997 and 2013, firms' headquarter county location is corrected for 13% (15%) of observations in our sample of customers (suppliers). For years before 1997, we update the county and state location of firms using the nearest available year in Infogroup.

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

lar, firms are required to disclose certain financial information for any industry segment that comprises more than 10% of consolidated yearly sales, assets, or profits as well as the identity of any customer representing more than 10% of the total reported sales.[18]

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 2013.[19] 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 and all their subsidiaries. We then select the best match by hand by inspecting the firm and customers' names and industries. Customers with no match are excluded from the sample.

Customers in our data set 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.[20] We discuss this selection issue in Section IV.E and show that our estimates hold when we consider alternative network structures that are not subject to this selection issue in Section A.3 of the Online Appendix to this paper.

III.C. 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

[18] While the data set also includes the variable that captures the annual sales of the reporting supplier to the reported customer, this information is provided on a voluntary basis and often imputed.

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

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

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 I, we are left with 41 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 22% of U.S. employment.[21] Figure I 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 II, 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.

III.D. Input specificity

We rely on three different proxies to measure the specificity of any given supplier. We first borrow from Rauch (1999) who classifies inputs into differentiated or homogeneous depending on whether they are sold on an organized exchange or not. This classification groups inputs into 1,189 industries classified according to the 4-digit SITC Rev. 2 system. Each industry is coded as being either sold on an exchange, reference priced, or homogeneous. We use the bridge between the SITC and SIC classification used in Feenstra (1996) to compute the share of differentiated goods produced in each industry. A supplier is thus considered as specific if it operates in an industry that lies above the median along this dimension. 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,

[21] 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 Online Appendix Table A.5).

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 three previous 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).[22]

III.E. Summary statistics

Table II presents summary statistics for our sample. Panel A presents the customer sample, which consists of 80,574 firm-quarters between 1978 and 2013. There are 2,051 firms in this sample. A firm is included in the sample in each quarter between three years before and three years after it appears as a customer in the Compustat Segment files. On average, a firm is reported by 1.38 suppliers in a given year. The main variables of interest are the growth in sales and cost of goods sold over the previous four quarters. The sample averages for these variables are 10.2% and 10.6%, and their medians are 4.0% and 3.8%. The probability that (at least) one of the suppliers of a given firm is hit by a natural disaster in any quarter is 1.4%. This compares with the probability of 1.6% that the customer is directly hit by a natural disaster.

There are, on average, seven years between the first and the last year a supplier reports a firm as a customer. The average sales of suppliers to their customers (identified with variable SALECS in the Compustat Segment files) represents around 2.5% 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 suggests 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 1,250 miles away from their customers, irrespective of

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

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.[23] 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 139,976 firm-quarters between 1978 and 2013. There are 4,686 firms in this sample. A firm is included in the sample in each quarter between three years before and three years after it reports another firm as a customer in the Compustat Segment files. These firms report an average of 0.7 customers. The main variable of interest is the growth in sales over the previous four quarters. The sample average for this variable is 18.8%, and the median is 4.5% . The probability that a firm in this sample is hit by a natural disaster in any quarter is 1.7%. The probability that one of a firm's customers is hit in any given quarter is 0.8%. Finally, the probability that one of its customers' suppliers is hit is 4.2%.

We investigate the distribution of suppliers and customers relative to the entire Compustat universe in Table A.12 of the Online Appendix. In Panel A, we present the number and share of quarter-firm per 48 Fama-French industries for suppliers, customers, and the Compustat universe. We do not find very large deviations across the three samples. This makes us confident that our sample is fairly representative of the Compustat universe. In Panel B, we further split the supplier and customer samples depending respectively on whether suppliers are hit or not, and whether customers are treated or not in a given quarter. Again, we do not find any patterns indicating that our estimates might be driven by any specific industry.

[23] 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.

IV. Results

IV.A. 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.[24] 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 previous year) on a series of dummies indicating whether a major natural disaster hits the firm in each of the current and previous five quarters, as well as fiscal-quarter, year-quarter and firm fixed effects. The results are presented in Table III. In column (1), the coefficient on the dummies indicating that a disaster hits the firm in the previous three quarters are negative and significant, ranging from 3.3 to 4.5 percentage points, which indicates that suppliers' sales growth drops significantly for three consecutive quarters following a disaster. We introduce controls for size, age, and profitability interacted with year-quarter fixed effects in column (2). The coefficient 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 state$\times$year fixed effects and industry$\times$year fixed effects. The effect goes down slightly in magnitude but remains significant in quarter (t-1). 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,

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

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 IV 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 previous four quarters), a dummy taking the value of one if the firm is specific, and the interaction between the two. We run the same regression for our three measures of input specificity. The coefficient on the interaction term is always positive, although not statistically significant, which suggests that shocks to specific suppliers are, if anything, of smaller magnitude than shocks to non-specific suppliers.[25]

IV.B. 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 V, which compares the growth in sales (relative to the same quarter in the previous 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 V, Equation 1, and present the results in Table V. In Panel A, we consider the effect of input disruption on sales growth. The variable of interest is the dummy *Disaster hits one supplier (t-4)*, which takes the value of one if (at least) one of the firm's suppliers is hit by a natural disaster in quarter $t-4$, and zero otherwise. The estimates in column (1) indicate that sales growth drops by 3.1 percentage points. Given the sample mean of 10%, the estimate is economically large. In column (2), we introduce controls for lagged size, age, and profitability, interacted

[25]The coefficient on *Specific firm* is omitted in columns (1) and (2) because firms' industry classification is fixed over time and is therefore absorbed by firm fixed effects.

with year-quarter fixed effects. The estimate decreases slightly to 2.7 percentage points and remains significant. In column (3), 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. In column (4), we add industry×year fixed effects. The point estimate is 1.9 percentage points, which suggests that the effect is not driven by an industry-wide shock. Across specifications, the coefficient on the dummy *Disaster hits firm (t-4)* is negative, which reflects the finding presented in Table III. 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 25% with respect to the sample average. Since suppliers in the sample represent approximately 2.5% 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 current and the previous five quarters. The results presented in Table VI indicate that the coefficient in the same quarter of the previous year (*Disaster hits one firm (t-4)*) is the largest in absolute value. No 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-1), see Table III). 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 that 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 current or previous four quarters. The regression also includes terciles of the number of suppliers, 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 (6)). 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 A.2 of the Online Appendix. 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 VII, 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 V) and statistically significant in all specifications.[26]

Another concern is that the estimates from Table V 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 headquarters' county locations of all suppliers once in a relationship with the firm is hit by

[26]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 2013.

a natural disaster. If the effects that we are picking up in Table V 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 VII. 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.

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. 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 VIII. 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 generally 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.

Robustness. We perform a number of robustness tests and present the results in the Online Appendix. We start with an additional test of the parallel trend assumption, which consists of estimating the difference-in-differences specification using only observations of eventually treated firms. We show in Table A.3 that our results are similar to those in Table V when we restrict the sample to eventually treated customer firms. One might also be concerned that firms with many suppliers and firms with few suppliers could be subject to differential trends. We augment the baseline regression with dummies indicating terciles of the number of firms' suppliers interacted with year-quarter fixed effects and present the results in Table A.4. The estimates remain stable, which indicates that the results are driven by the treatment rather than the number of firms' links.

We next 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 first 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.5. 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 > 50% *sales abroad*, which takes the value of one if the customer firm reports sales abroad that represent more than 50% 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 of 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 also check whether our results are not driven by large natural disasters through their effect at the sector level. If sectors tend to be clustered geographically so that all firms tend to be affected by natural disasters, then the effects we are picking up should be interpreted as sector-specific rather than firm-specific shocks. In our sample, the average and median share of affected sales at the 4-digit SIC level are 19% and 8% respectively. We interact the dummy *Disaster hits one supplier* with various dummies for whether more than 10%, 30%, or 50% of the supplier's 4-digit SIC sector is affected by the disaster. If what we are picking up is the effect of disruptions to geographically clustered sectors, the coefficient on the interaction term should increase with the share of the sector being affected. We find in Table A.6 that this is not the case.

We also check that our estimates are not sensitive to the 300 miles cutoff we use to exclude supplier-customers that are geographically close. In Table A.7, we vary this cutoff from 0 to 500 miles and find that the results remain unchanged. We also find results similar to the baseline in Table A.8, where we only consider treatments when the customer and supplier are never jointly hit by a disaster in the same quarter throughout the sample period. In Table A.9, we also control for linkages across firms via product- and input-market competition and find virtually identical estimates of the coefficient on our main variable of interest, *Disaster hits a supplier*. We show in Table A.10 that the coefficients go down slightly but remain significant when we weight regressions by customers' size (inflation-adjusted sales). This ensures that the effects we are picking up are not concentrated among the smallest of the customers in our sample. Finally, we confirm in Table A.11 that the estimates are robust to an alternative definition of our main dependent variable, namely, the difference in the logarithm of firm sales.

IV.C. 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 VI 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.

Returns analysis. 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.[27] We find 1,082 events satisfying the above requirements. For each firm-disaster pair, we then estimate daily abnormal stock returns using the Fama-French three-factor model:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + s_i \; SMB_t + h_i \; HML_t + \epsilon_{i,t}, \tag{2}$$

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.[28] The three-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:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{M,t} + \hat{s}_i SMB_t + \hat{h}_i HML_t) \tag{3}$$

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 – $[-10,-1]$, $[0,10]$, $[11,20]$, $[21,30]$, $[31,40]$, and $[-10,40]$, where $[t_0 = -10, T = 40]$ is a 51 trading days window starting 10 trading days before the event date – to obtain cumulative average abnormal returns (CAAR). Formally,

[27] 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.

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

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

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, Masumeci and Poulsen (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.[29]

Results. Table IX, illustrated in Figure VI, 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 and untreated firms, i.e., for which all linked suppliers are not affected by a given major disaster. CAAR for treated customer firms on the 51 trading days event window $[t_0 = -10, T = 40]$ 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. A large fraction of this drop occurs in the 21 trading days $[t_0 = -10, T = 10]$ around the event, for which CAAR are highly statistically significant, which is consistent with investors quickly reacting to the news.[30] These findings indicate that firms' sales are not simply postponed in reaction to input disruptions but materialize into sizable value losses.

[29] 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.

[30] Earthquakes' striking dates might be considered truly unexpected events. However, in the case of 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.

We find that directly affected suppliers experience an abnormal drop in returns of around 2.5% over the same event window. In the third column of Table IX, 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 X presents the results separately for events affecting specific and non-specific suppliers. For our three measures of input specificity, we find that firms experience a larger drop in returns when disasters hit their *specific* suppliers than their non-specific ones.

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

IV.D. Horizontal propagation: effect on related suppliers

In this section, we explore whether the effects documented above spill over to other related suppliers that are not *directly* affected by the natural disaster but only *indirectly* through their common relationship with the same customer.[31] Going back to the setting described in Section II, we are interested in the response of S2 to the drop in C's sales triggered by a disruption to S1's production.

Note that the direction of the effect is unclear. It could either be positive or negative, depending on the degree of complementarity across intermediate input suppliers. If intermediate inputs are strong substitutes, the response might be positive, that is, the disruption of supplier leads to an increase in sales growth of other suppliers servicing the same customer. Conversely, when they are complement, related suppliers could experience a decrease in sales,

[31] The nature of our data limits our ability to precisely estimate the effect of disruptions on customers' customers: there are only 0.12% of the observations in our sample for which the dummy *Disasters hits a supplier's supplier* takes the value 1. The alternative network structure we obtain from Capital IQ (see Section A.3 in the Online Appendix) is not subject to this limitation. In that case, there are 9.9% of the observations for which the dummy *Disasters hits a supplier's supplier* takes the value 1. In Table A.19, we run this analysis and find that the effect on sales growth of disruptions affecting a firm's suppliers' supplier is negative but insignificant.

in particular if they cannot easily shift their production to other customers. To estimate the direction of the effect, we run the OLS specification presented in Section II in the sample of suppliers.

The results are presented in Table XI. In column (1), the coefficient on *Disaster hits one customer's supplier* is a negative and significant 3.8 percentage point decrease in sales growth. This is consistent with substantial negative spillovers to related suppliers. In line with Table III, the coefficient on *Disaster hits firm (t-4,t-1)* 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 XI 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 XII, 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 XII, 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 XI 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 XII, 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.

IV.E. Discussion

A general equilibrium network model. In Section A.1 of the Online Appendix, we present a general equilibrium network model based on Long and Plosser (1983) and Acemoglu et al. (2012) that delivers predictions of the magnitude of the pass-through of suppliers' disruptions to their customers (vertical propagation) and the other suppliers of their customers (horizontal propagation).[32] Firms have constant-returns-to-scale production functions and choose the quantities of labor and intermediate inputs in order to maximize profits, while households provide labor and consume. We model the effect of natural disasters as the destruction of a small fraction of the output of impacted firms. We express the pass-through of supply disruptions to any given firm as the ratio of its sales drop to the disrupted supplier's

[32] Within our framework, horizontal propagation combines the effect of the demand feedback effect from the common customer and the effect of complementarity across suppliers of intermediate inputs. See Grossman and Rossi-Hansberg (2008) for a framework that allows for a clear decomposition of both channels.

sales drop, as a function of model parameters. In Online Appendix A.1B we present and discuss the predicted value of the downstream and horizontal pass-throughs, as well as the ratio of both pass-throughs, as a function of σ, the elasticity of substitution across intermediate input suppliers.[33] We then compare these pass-throughs to the ratio of the estimates we obtain from Table VI and XI, namely, a downstream pass-through close to $2\%/4\% = 0.5$, a horizontal pass-through close to $3.8\%/4\% = 0.95$, and a ratio of the horizontal over downstream pass-through of $0.95/0.5 = 1.9$. Our empirical estimates are comparable, yet slightly higher, to the predictions of the model for values of σ nearing 0, the Leontief limit, which are 0.3, 0.5, and 1.5 respectively. Our reduced-form coefficients are therefore consistent with the predictions of a network model with high levels of complementarity across intermediate input suppliers.

Sample representativeness. An important concern with the network production data used in this paper is that it includes relationships where the customer typically represents more than 10% of the sales of the supplier and where both firms are publicly listed. Even though the firms we consider are the largest in the economy, this double selection issue might introduce some bias in our estimates. A priori, the fact that we are missing some suppliers introduces noise, which is likely to bias the results against finding any sort of propagation.[34] Nonetheless, in Section A.3 of the Online Appendix, we go one step further to ensure that this selection issue is not driving the results. We replicate our results using an alternative network structure that is not prone to the selection issues highlighted above. We consider an alternative firm-level data set obtained from Capital IQ, which provides firm-to-firm relationships based on regulatory filings as well as press reports and is therefore not subject to the 10% reporting threshold. Reassuringly, we find similar estimates when we

[33] We set the share of intermediate inputs to 0.55, the elasticity of substitution between labor and intermediate inputs to 1, and the cross-firm elasticity of demand to 2. See Online Appendix A.1B for discussions of parameter values and of the sensitivity of model predictions to these values.

[34] Moreover, Atalay et al. (2011) use this data and show that the truncation issue does not affect the shape of the in-degree distribution: the fraction of suppliers of each customer that we miss because of the 10% threshold is similar for customers with many or few suppliers.

run our baseline tests using this network data (see columns (1) and (2) of Online Appendix Table A.17). In addition, we show that downstream propagation does not depend on whether the supplier is publicly listed or not, and that horizontal propagation does not depend on whether the customer is publicly listed or not (see columns (3) and (4) of Table A.17). A limitation of our study is that we cannot observe the output growth of privately held firms. Reassuringly, we find similar estimates when we consider the effect of supply disruptions at the industry level (Online Appendix Table A.20) or at the industry × state level (Online Appendix Table A.21).

Measurement of output. The benefit of using Compustat data is that it allows us to measure sales growth at the quarterly frequency. While we cannot disentangle quantity from prices from Compustat data, we also find significant effects of intermediate input disruptions on real output growth when we perform our analyses at the industry level (Online Appendix Table A.20). A related concern is that we cannot measure value added from Compustat. Hence, we cannot disentangle from the drop in sales what comes from the drop in value added and what comes from the drop in intermediate input use. The finding that state × industry GDP growth reacts to intermediate input disruptions (Online Appendix Table A.21) suggests that supply shocks ultimately reduce downstream value added.[35]

Role of inventories. Inventories typically serve as a buffer for production. One might expect differential patterns of propagation depending on whether firms hold high or low inventories. We first ask whether suppliers holding high levels of inventories tend to experience the drop in sales growth later than those holding little inventories. In Table A.13 in the Online Appendix, we find that high inventory suppliers experience their largest drop in sales growth in quarter (t-2), one quarter later than low inventory suppliers who experience

[35]In addition, we find in Table A.16 in the Online Appendix that the ratio of sales to capital and labor goes down following intermediate input disruptions. Hence, in contrast to Costinot, Vogel and Wang (2013) who assume that downstream errors (or disasters) are more costly because they destroy a longer chain of value added, our results suggest that upstream errors are more costly because they prohibit downstream tasks from being performed. We thank an anonymous referee for highlighting this point.

it in quarter (t-1). We then turn to regressions at the customer level. Given what we found at the supplier level, we would expect the effect to kick in later for customers sourcing from high inventory suppliers. In Table A.14, we split the *Disaster hits supplier* dummy into two dummies indicating whether a disaster hits a high or low inventory supplier. We find that the drop in sales growth occurs in quarters (t-3) and (t-4) when a low inventory supplier is hit, while it occurs in quarters (t-4) and (t-5) when a high inventory supplier is hit. This illustrates that inventories delay the propagation of supply shocks in production networks.

Economic significance. We first note that treated firms in our sample make up a large share of the U.S. economy. In any given quarter, eventually treated firms represent 36% and 43% of total Compustat sales and total stock market value respectively. In quarters when natural disasters hit the U.S. territory, treated firms represent on average 9% of both total Compustat sales and total stock market value, which is economically significant. By contrast eventually-hit suppliers represent 12% and 15% of total Compustat sales and stock market value respectively in an average quarter, and affected suppliers represent on average 1% of both total Compustat sales and total stock market value in quarters when a disaster hits. Another way to assess the economic importance of propagation is to compare the 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 following 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 \$246 billion for suppliers and \$580 billion for customers. Hence, \$1 of lost sales at the supplier level leads to \$2.4 of lost sales at the customer level in our sample. This suggests that relationships in production networks substantially amplify idiosyncratic shocks. Whether or not this amplification mechanism is powerful enough to generate fluctuations in aggregate output is a question that we leave to future research.

Trends in input specificity. Figure VII 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 reference 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.

External validity. 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.[36] 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 results to be obtained within a firm, when the division producing a specific part of the final good is hit by a shock. Yet 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. In fact, we show in Table A.15 in the Online Appendix that propagation tends to be weaker when disasters hit areas that are frequently hit in our sample. While this is a nice confirmation that production networks react more strongly to shocks that are less likely to be anticipated,

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

this also suggests that one should be cautious in extrapolating our findings to estimate the impact of larger shocks, if firms devote more resources to shelter themselves against those than against natural disasters.

V. 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 to 3 percentage points in sales growth following the event, which amounts to a 25% 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 it 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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VI. Graphs and tables

TABLE I

List of Major Disasters

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
Opal	October 1995	186	6.43	AL, FL, GA, LA, MS, NC, SC
Blizzard	January 1996	319	14.57	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	15.68	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Allison	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	311	12.47	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Ivan	September 2004	284	7.31	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
Jeanne	September 2004	160	8.8	DE, FL, GA, MD, NC, NJ, PA, SC, VA
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	98	1.79	AR, LA, MS
Ike	September 2008	163	4.11	AR, LA, MO, TN, TX
Blizzard Groundhog Day	February 2011	210	14.63	CT, IA, IL, IN, KS, MA, MO, NJ, NM, NY, OH, OK, PA, TX, WI
Irene	August 2011	40	3.19	CT, MA, MD, NC, NJ, NY, VA, VT
Tropical Storm Lee	September 2011	110	5.23	AL, CT, GA, LA, MD, MS, NJ, NY, PA, TN, VA
Isaac	August 2012	77	3.36	FL, LA, MS
Sandy	October 2012	274	22.08	CT, DE, MA, MD, NC, NH, NJ, NY, OH, PA, RI, VA, WV
Flooding and Severe Weather- Illinois	April 2013	29	3.11	IL, IN, MO
Flooding- Colorado	September 2013	8	0.92	CO

Notes. This table describes the 41 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 2013.

TABLE II

Descriptive Statistics

Panel A:	Customer Sample					
	Obs.	Mean	Std. Dev.	p1	p50	p99
Sales growth (t-4,t)	80574	0.102	0.375	-0.606	0.040	1.927
Cogs growth (t-4,t)	79358	0.106	0.411	-0.651	0.038	2.193
Disaster hits firm (t)	80574	0.016	0.126	0.000	0.000	1.000
Disaster hits one supplier (t)	80574	0.014	0.118	0.000	0.000	1.000
Number of suppliers	80574	1.383	4.162	0.000	0.000	19.000
	DIFF.		R&D		PATENT	
	S	NS	S	NS	S	NS
Av. duration of relationships	7.125	6.692	6.373	8.335	7.821	6.618
Av. supplier-customer HQs distance	1332	1210	1502	1214	1388	1219
Av. suppliers' input share	0.022	0.025	0.017	0.023	0.025	0.022
	Eventually Treated			Never Treated		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Assets	32061	12656	20013	48513	3254	7099
Age	32061	27.822	16.623	48513	19.233	15.680
ROA	32061	0.145	0.091	48513	0.118	0.128

Panel B:	Supplier Sample					
	Obs.	Mean	Std. Dev.	p1	p50	p99
Sales growth (t-4,t)	139976	0.188	0.814	-0.876	0.045	4.568
Disaster hits firm (t)	139976	0.017	0.127	0.000	0.000	1.000
Disaster hits a customer (t)	139976	0.008	0.088	0.000	0.000	0.000
Disaster hits a customer's supplier (t)	139976	0.042	0.200	0.000	0.000	1.000
Number of customers	139976	0.711	0.964	0.000	0.000	4.000
% Employees at HDQs' county	102279	0.597	0.365	0.000	0.667	1.000

Notes. This table presents the summary statistics for our sample. Panel A presents the customer sample, which consists of 80,574 firm-quarters between 1978 and 2013. There are 2,051 firms in this sample. A firm is included in the customer sample for each quarter between three years before the first year and three years after the 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 previous 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 supplier is considered as specific if its industry lies above the median of the share of differentiated goods according to the classification provided by Rauch (1999). 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 three years is above the median. The last part of Panel A compares the size, age, and return on assets (ROA) of eventually treated firms, namely, those with suppliers that are hit by a major natural disaster at least once over the sample period, and never treated firms. Panel B presents the supplier sample, which consists of 139,976 firm-quarters between 1978 and 2013. There are 4,686 firms in this sample. A firm is included in the supplier sample for each quarter between three years before the first year and three years after the 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 previous year.

TABLE III

Natural Disaster Disruptions – Supplier Sales Growth

	Sales Growth $(t-4, t)$			
Disaster hits firm (t)	-0.006	-0.004	-0.001	-0.011
	(0.018)	(0.018)	(0.018)	(0.018)
Disaster hits firm (t-1)	-0.045***	-0.045***	-0.032*	-0.039**
	(0.016)	(0.016)	(0.017)	(0.018)
Disaster hits firm (t-2)	-0.033*	-0.032*	-0.024	-0.026
	(0.018)	(0.018)	(0.021)	(0.021)
Disaster hits firm (t-3)	-0.042**	-0.040**	-0.032	-0.029
	(0.019)	(0.019)	(0.022)	(0.023)
Disaster hits firm (t-4)	-0.031	-0.028	-0.029	-0.024
	(0.020)	(0.020)	(0.022)	(0.023)
Disaster hits firm (t-5)	-0.007	-0.005	-0.022	-0.019
	(0.020)	(0.020)	(0.023)	(0.023)
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA $\times$ Year-Quarter FE	No	Yes	Yes	Yes
State-Year FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
Observations	139976	139976	139976	139976
R^2	0.177	0.192	0.212	0.233

Notes. This table presents estimates from panel regressions of firms' sales growth relative to the same quarter in the previous year on a dummy indicated whether the firm is hit by a major disaster in the current and each of the previous five quarters. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. In columns (2) to (4), we also control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. In columns (3) and (4), we include state dummies interacted with year dummies. In column (4), we include 48 Fama-French industry 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 II, Panel B) between 1978 and 2013. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE IV

Natural Disasters Disruptions – Specific vs. Non-specific Suppliers

	Sales Growth $(t-4,t)$					
Supplier specificity:	DIFF.		R&D		PATENT	
Disaster hits firm (t-4,t-1)	-0.050***	-0.044***	-0.048***	-0.048***	-0.046***	-0.041***
	(0.017)	(0.016)	(0.012)	(0.012)	(0.016)	(0.015)
Disaster hits specific firm (t-4,t-1)	0.023	0.013	0.038	0.044	0.020	0.011
	(0.026)	(0.026)	(0.040)	(0.039)	(0.028)	(0.028)
Specific firm			0.099***	0.090***	-0.060***	-0.030**
			(0.021)	(0.021)	(0.014)	(0.013)
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	139976	139976	139976	139976	139976	139976
R^2	0.177	0.192	0.177	0.192	0.177	0.192

Notes. This table presents estimates from panel regressions of firms' sales growth relative to the same quarter in the previous year on a dummy indicated whether the firm is hit by a major disaster in one of the previous four quarters. In columns (1) and (2), a firms is considered as specific if its industry lies above the median of the share of differentiated goods according to the classification provided by Rauch (1999). 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 three years is above the median. All regressions include fiscal-quarter, year-quarter, and firm fixed effects. In columns (2), (4), and (6), we 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 supplier sample (described in Table II, Panel B) between 1978 and 2013. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE V

Downstream Propagation – Baseline

Panel A:	Sales Growth $(t-4, t)$			
Disaster hits one supplier (t-4)	-0.031***	-0.027***	-0.029***	-0.019**
	(0.009)	(0.008)	(0.008)	(0.008)
Disaster hits firm (t-4)	-0.031***	-0.029***	-0.005	-0.003
	(0.011)	(0.011)	(0.009)	(0.009)
Number of Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA $\times$ Year-Quarter FE	No	Yes	Yes	Yes
State-Year FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
Observations	80574	80574	80574	80574
R^2	0.234	0.262	0.300	0.342
Panel B:	**Cost of Goods Sold Growth $(t-4, t)$**			
Disaster hits one supplier (t-4)	-0.031***	-0.028***	-0.029***	-0.020**
	(0.010)	(0.010)	(0.010)	(0.010)
Disaster hits firm (t-4)	-0.014	-0.013	0.001	0.002
	(0.012)	(0.012)	(0.011)	(0.011)
Number of Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA $\times$ Year-Quarter FE	No	Yes	Yes	Yes
State-Year FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
Observations	79358	79358	79358	79358
R^2	0.188	0.215	0.253	0.290

Notes. This table presents estimates from panel regressions of firms' sales growth (Panel A) or cost of goods sold growth (Panel B) relative to the same quarter in the previous year on a dummy indicating whether (at least) one of their suppliers is hit by a major disaster in the same quarter of the previous year. All regressions include a dummy indicating whether the firm itself is hit by a major disaster in the same quarter of the previous year as well as fiscal-quarter, year-quarter, and firm fixed effects. All regressions also control for the number of suppliers (dummies indicating terciles of the number of suppliers). In columns (2) to (4), we control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. In columns (3) and (4), we include state dummies interacted with year dummies. In column (4), we include 48 Fama-French industry dummies interacted with year dummies. Regressions contain all firm-quarters of our customer sample (described in Table II, Panel A) between 1978 and 2013. Standard errors presented in parentheses are clustered at the firm-level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE VI

Downstream Propagation – Sales Growth Dynamics

	Sales Growth $(t-4,t)$			
Disaster hits one supplier (t)	-0.012	-0.010	-0.007	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)
Disaster hits one supplier (t-1)	-0.013	-0.013	-0.011	-0.004
	(0.008)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t-2)	-0.013	-0.009	-0.010	0.002
	(0.009)	(0.009)	(0.010)	(0.010)
Disaster hits one supplier (t-3)	-0.028***	-0.025***	-0.025***	-0.013
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t-4)	-0.031***	-0.027***	-0.030***	-0.020**
	(0.009)	(0.009)	(0.009)	(0.009)
Disaster hits one supplier (t-5)	-0.016*	-0.013	-0.014	-0.007
	(0.010)	(0.010)	(0.010)	(0.010)
Disaster hits firm (t)	0.015	0.016	0.015	0.011
	(0.012)	(0.012)	(0.012)	(0.012)
Disaster hits firm (t-1)	-0.003	-0.003	0.001	-0.003
	(0.011)	(0.011)	(0.011)	(0.012)
Disaster hits firm (t-2)	-0.023**	-0.022**	-0.002	0.002
	(0.011)	(0.011)	(0.013)	(0.013)
Disaster hits firm (t-3)	-0.042***	-0.043***	-0.022*	-0.016
	(0.011)	(0.011)	(0.013)	(0.013)
Disaster hits firm (t-4)	-0.034***	-0.032***	-0.010	-0.006
	(0.012)	(0.011)	(0.013)	(0.013)
Disaster hits firm (t-5)	-0.026**	-0.027**	-0.010	-0.006
	(0.012)	(0.012)	(0.012)	(0.012)
Number of Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year-Quarter FE	No	Yes	Yes	Yes
State-Year FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
Observations	80574	80574	80574	80574
R^2	0.234	0.262	0.300	0.342

Notes. This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the previous year on dummies indicating whether (at least) one of their suppliers is hit by a major disaster in the current and each of the previous five quarters. All regressions include dummies indicating whether the firm itself is hit by a major disaster in the current and each of the previous five quarters, as well as fiscal-quarter, year-quarter and firm fixed effects. All regressions also control for the number of suppliers (dummies indicating terciles of the number of suppliers). In columns (2) to (4), we control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. In columns (3) and (4), we include state dummies interacted with year dummies. In column (4), we include 48 Fama-French industry dummies interacted with year dummies. Regressions contain all firm-quarters of our customer sample (described in Table II, Panel A) between 1978 and 2013. Standard errors presented in parentheses are clustered at the firm-level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE VII

DOWNSTREAM PROPAGATION – ROBUSTNESS

Panel A:	Sales Growth $(t-4, t)$			
Disaster hits more than 10% of firm's workforce (t-4)	-0.006	-0.005	0.002	0.009
	(0.010)	(0.010)	(0.010)	(0.010)
Disaster hits one supplier (t-4)	-0.031***	-0.027***	-0.030***	-0.020**
	(0.009)	(0.009)	(0.009)	(0.008)
Disaster hits firm (t-4)	-0.027**	-0.026**	-0.006	-0.009
	(0.012)	(0.012)	(0.011)	(0.011)
Number of Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year-Quarter FE	No	Yes	Yes	Yes
State-Year FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
Observations	80574	80574	80574	80574
R^2	0.234	0.262	0.300	0.342

Panel B:	Sales Growth $(t-4, t)$			
Disaster hits *any eventually linked suppliers*' location (t-4)	0.003	0.004	0.004	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Disaster hits one supplier (t-4)	-0.033***	-0.029***	-0.032***	-0.023**
	(0.010)	(0.010)	(0.010)	(0.010)
Disaster hits firm (t-4)	-0.031***	-0.029***	-0.005	-0.003
	(0.011)	(0.011)	(0.009)	(0.009)
Number of Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year-Quarter FE	No	Yes	Yes	Yes
State-Year FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
Observations	80574	80574	80574	80574
R^2	0.234	0.262	0.300	0.342

Notes. This table presents estimates from panel regressions of firms' sales growth relative to the same quarter in the previous year on a dummy indicating whether (at least) one supplier is hit by a major disaster in the same quarter of the previous year. All regressions include a dummy indicating whether the firm itself is hit by a major disaster in the same quarter in the previous year 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. In columns (2) to (4), we control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. In columns (3) and (4), we include state dummies interacted with year dummies. In column (4), we include 48 Fama-French industry dummies interacted with year dummies. Regressions contain all firm-quarters of our customer sample (described in Table II, Panel A) between 1978 and 2013. Standard errors presented in parentheses are clustered at the firm-level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE VIII

Downstream Propagation – Input Specificity

	Sales Growth $(t-4, t)$					
Supplier specificity:	DIFF.		R&D		PATENT	
Disaster hits one non-specific supplier (t-4)	-0.002	-0.002	-0.018	-0.011	-0.020*	-0.016
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Disaster hits one specific supplier (t-4)	-0.050***	-0.043***	-0.039***	-0.032**	-0.039***	-0.034***
	(0.010)	(0.010)	(0.014)	(0.014)	(0.011)	(0.012)
Disaster hits firm (t-4)	-0.031***	-0.029***	-0.031***	-0.029***	-0.031***	-0.029***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Number of Suppliers	Yes	Yes	Yes	Yes	Yes	Yes
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	80574	80574	80574	80574	80574	80574
R^2	0.234	0.262	0.234	0.261	0.234	0.262

Notes. This table presents estimates from panel regressions of firms' sales growth relative to the same quarter in the previous year 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 same quarter of the previous year. In columns (1) and (2), a supplier is considered as specific if its industry lies above the median of the share of differentiated goods according to the classification provided by Rauch (1999). 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 three years is above the median. All regressions include a dummy indicating whether the firm itself is hit by a major disaster in the same quarter in the previous year as well as fiscal-quarter, year-quarter, and firm fixed effects. All regressions also control for the number of suppliers (dummies indicating terciles of the number of suppliers). In columns (2), (4), and (6), we control for firm-level characteristics (dummies indicating terciles of size, age, and ROA respectively) interacted with year-quarter dummies. Regressions contain all firm-quarters of our customer sample (described in Table II, Panel A) between 1978 and 2013. Standard errors presented in parentheses are clustered at the firm-level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE IX

Downstream Propagation – Effect on Firm Value

	CAAR		
	Customers (N=1082)	Suppliers (Direct effect) (N=2004)	Customers (Control group) (N=6379)
$[-10, -1]$	-0.487	-0.195	-0.176**
	(-1.283)	(-0.819)	(-2.310)
$[0, 10]$	-0.361*	-0.548**	-0.124
	(-1.911)	(-2.215)	(-0.302)
$[11, 20]$	-0.177	-1.452***	-0.029
	(-0.269)	(-3.340)	(-0.205)
$[21, 30]$	-0.121	-0.385	-0.006
	(-0.583)	(-1.088)	(0.392)
$[31, 40]$	0.014	0.120	-0.042
	(-0.215)	(1.123)	(-1.208)
$[-10, 40]$	-1.132**	-2.459***	-0.379
	(-1.982)	(-3.029)	(-1.563)

Notes. 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 three-factor Fama-French model over the interval from 260 to 11 trading days before the event date. We exclude firm-disaster observations with missing returns in the estimation or event windows, when the firm itself is hit by the disaster, or when the firm or one of its suppliers are hit by another major disaster in the 30 trading days around the event. ADJ-BMP t-statistics, presented in parentheses, are computed with the standardized cross-sectional method of Boehmer, Masumeci and Poulsen (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, namely, 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 2013. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

TABLE X

Downstream Propagation – Input Specificity and Effect on Firm Value

	Customers' CAAR when disaster hits at least one supplier					
Supplier specificity:	DIFF.		R&D		PATENT	
	N=628	N=454	N=318	N=764	N=375	N=707
At least one specific supplier	Yes	No	Yes	No	Yes	No
$[-10,-1]$	-0.885	0.064	-0.321	-0.556	-0.096	-0.694*
	(-1.567)	(-0.288)	(-0.568)	(-1.243)	(0.164)	(-1.731)
$[0,10]$	-0.636***	0.018	-0.621	-0.253	-0.651***	-0.208
	(-2.757)	(-0.022)	(-1.395)	(-1.542)	(-2.585)	(-0.742)
$[11,20]$	-0.168	-0.189	0.181	-0.326	0.177	-0.365
	(-0.608)	(0.250)	(1.482)	(-1.021)	(0.479)	(-0.674)
$[21,30]$	-0.460	0.348	-1.351**	0.391	-0.560	0.112
	(-1.017)	(0.192)	(-2.349)	(0.564)	(-0.502)	(-0.421)
$[31,40]$	-0.219	0.337	-0.340	0.162	-0.391	0.229
	(-0.331)	(0.006)	(-0.896)	(0.213)	(-0.381)	(-0.038)
$[-10,40]$	-2.368***	0.578	-2.452*	-0.582	-1.519	-0.926*
	(-2.939)	(0.080)	(-1.769)	(-1.412)	(-1.285)	(-1.690)

Notes. 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 its industry lies above the median of the share of differentiated goods according to the classification provided by Rauch (1999). 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 three years is above the median. Abnormal returns are computed after estimating, for each firm-disaster pair, a three-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, Masumeci and Poulsen (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010). The sample period is from 1978 to 2013. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively.

TABLE XI

Horizontal Propagation – Related Suppliers' Sales Growth

	Sales Growth ($t-4, t$)			
Supplier specificity:		DIFF.	R&D	PATENT
Disaster hits firm (t-4,t-1)	-0.040***	-0.040***	-0.041***	-0.040***
	(0.013)	(0.013)	(0.013)	(0.013)
Disaster hits one customer (t-4,t-1)	0.002	0.001	0.001	0.002
	(0.021)	(0.021)	(0.021)	(0.021)
Disaster hits one customer's supplier (t-4,t-1)	-0.038***			
	(0.010)			
Disaster hits one customer's specific supplier (t-4,t-1)		-0.047***	-0.048***	-0.040***
		(0.013)	(0.014)	(0.013)
Disaster hits one customer's non-specific supplier (t-4,t-1)		-0.011	-0.013	-0.015
		(0.013)	(0.013)	(0.013)
Number of Customers' Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA $\times$ Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	139976	139976	139976	139976
R^2	0.192	0.192	0.192	0.192

Notes. This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the previous year on one dummy indicating whether one of the firm's customers' other suppliers is hit by a major disaster in the previous four quarters. Columns (2) to (4) split customers' other suppliers into specific and non-specific suppliers. All regressions include two dummies indicating whether the firm itself is hit in the previous four quarters and whether one of the firm's customer is hit in the previous four quarters. All regressions also control for the number of customers' suppliers (dummies indicating terciles of the number of customers' suppliers). All regressions include fiscal-quarter, year-quarter, and firm fixed effects as well as 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 II, Panel B) between 1978 and 2013. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

TABLE XII

Horizontal Propagation – Robustness

	Supplier's Sales Growth $(t-4,t)$			
Panel A:		DIFF.	R&D	PATENT
Disaster hits at least 10% of firm's workforce (t-4,t-1)	-0.007	-0.007	-0.008	-0.007
	(0.016)	(0.016)	(0.016)	(0.016)
Disaster hits firm (t-4,t-1)	-0.035*	-0.035**	-0.035*	-0.035**
	(0.018)	(0.018)	(0.018)	(0.018)
Disaster hits one customer (t-4,t-1)	0.002	0.001	0.001	0.002
	(0.021)	(0.021)	(0.021)	(0.021)
Disaster hits one customer's supplier (t-4,t-1)	-0.038***			
	(0.010)			
Disaster hits one customer's specific supplier (t-4,t-1)		-0.047***	-0.048***	-0.040***
		(0.013)	(0.014)	(0.013)
Disaster hits one customer's non-specific supplier (t-4,t-1)		-0.011	-0.013	-0.015
		(0.013)	(0.013)	(0.013)
Panel B:		DIFF.	R&D	PATENT
Disaster hits *any customers' eventually linked suppliers*' location (t-4,t-1)	-0.022*	-0.022*	-0.022	-0.022*
	(0.013)	(0.013)	(0.013)	(0.013)
Disaster hits firm (t-4,t-1)	-0.040***	-0.041***	-0.041***	-0.041***
	(0.013)	(0.013)	(0.013)	(0.013)
Disaster hits one customer (t-4,t-1)	0.002	0.002	0.001	0.002
	(0.021)	(0.021)	(0.021)	(0.021)
Disaster hits one customer's supplier (t-4,t-1)	-0.038***			
	(0.010)			
Disaster hits one customer's specific supplier (t-4,t-1)		-0.047***	-0.048***	-0.039***
		(0.013)	(0.014)	(0.013)
Disaster hits one customer's non-specific supplier (t-4,t-1)		-0.011	-0.013	-0.015
		(0.013)	(0.013)	(0.013)
Observations	139976	139976	139976	139976
R^2	0.192	0.192	0.192	0.192

TABLE XII (continued)

Panel C:	Sales Growth $(t-4,t)$			
		DIFF.	R&D	PATENT
Disaster hits *any eventually linked customer's* supplier (t-4,t-1)	-0.008	-0.005	-0.019	-0.012
	(0.016)	(0.014)	(0.012)	(0.014)
Disaster hits firm (t-4,t-1)	-0.039***	-0.040***	-0.038***	-0.039***
	(0.013)	(0.013)	(0.013)	(0.013)
Disaster hits one customer (t-4,t-1)	0.003	0.002	0.004	0.004
	(0.021)	(0.021)	(0.021)	(0.021)
Disaster hits one customer's supplier (t-4,t-1)	-0.032*			
	(0.016)			
Disaster hits one customer's specific supplier (t-4,t-1)		-0.044***	-0.041***	-0.036***
		(0.014)	(0.015)	(0.013)
Disaster hits one customer's non-specific supplier (t-4,t-1)		-0.008	-0.003	-0.008
		(0.015)	(0.014)	(0.015)
Number of Customers' Suppliers	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Size, Age, ROA × Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	139976	139976	139976	139976
R^2	0.192	0.192	0.192	0.192

Notes. This table presents estimated coefficients from panel regressions of firms' sales growth relative to the same quarter in the previous year on one dummy indicating whether one of the firm's customers' other suppliers is hit by a major disaster in the four previous 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 four previous 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 four previous 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 four previous quarters. Columns (2) to (4) split customers' other suppliers into specific and non-specific suppliers. All regressions include two dummies indicating whether the firm itself is hit in the previous four quarters and whether one of the firm's customer is hit in the previous four quarters. All regressions also control for the number of customers' suppliers (dummies indicating terciles of the number of customers' suppliers). All regressions include fiscal-quarter, year-quarter, and firm fixed effects as well as 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 II, Panel B) between 1978 and 2013. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

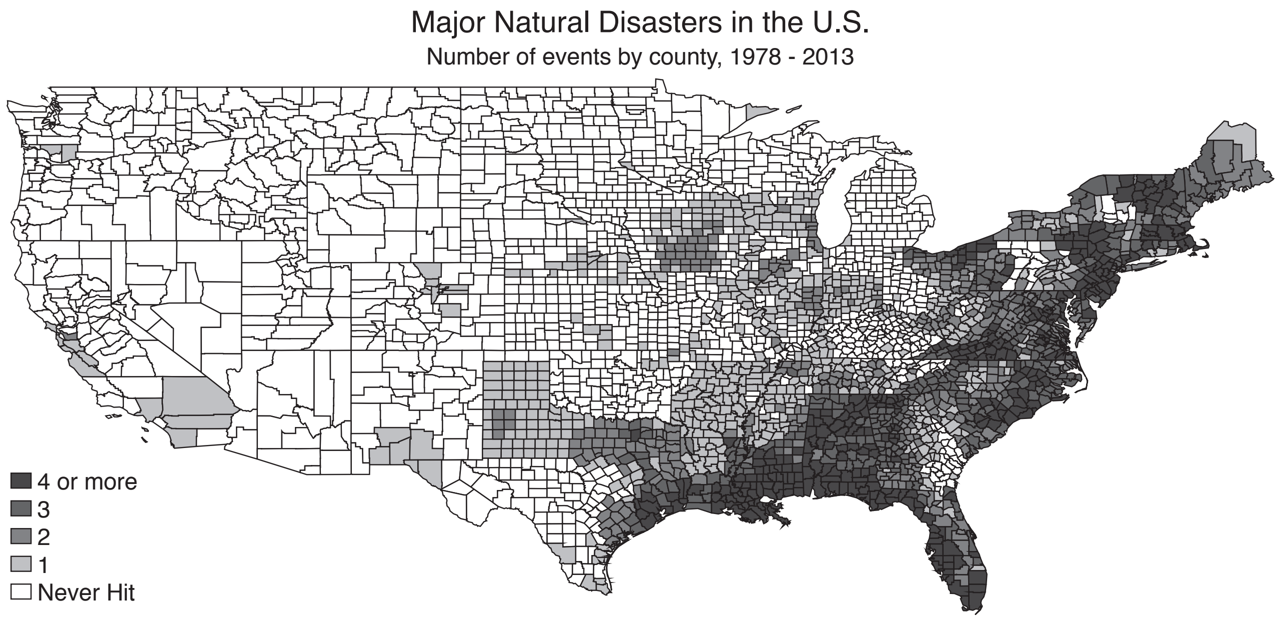

FIGURE I

Natural Natural Disasters Frequency by U.S. Counties

Notes. This map presents the number of major natural disaster 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 I describes the major natural disasters included in the sample.

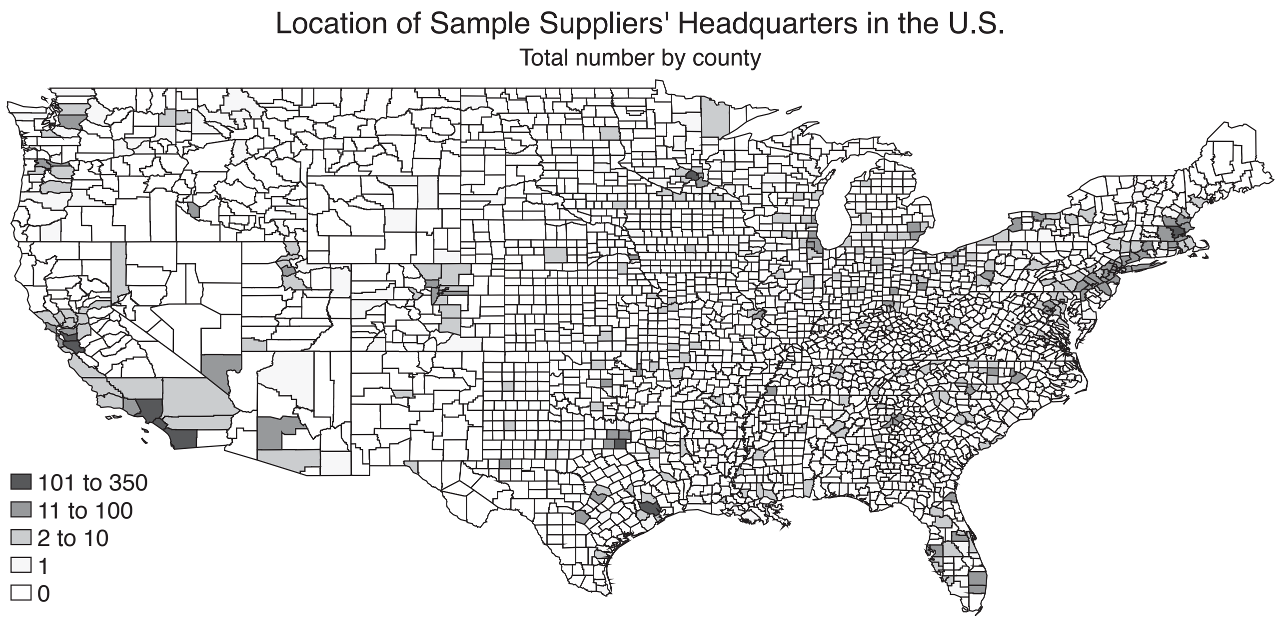

FIGURE II

Location of Sample Suppliers' Headquarters

Notes. This map presents for our sample the number of suppliers' headquarters located in each U.S. county. Data on the location of headquarters are obtained from Compustat and Infogroup databases.

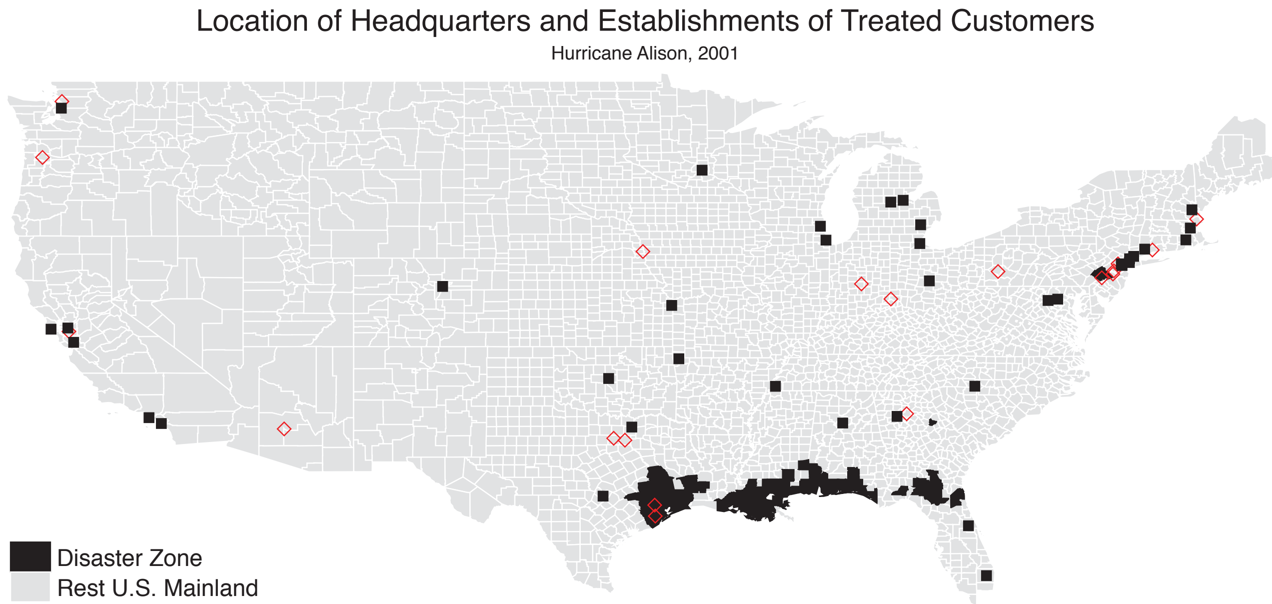

FIGURE III

Illustration of Empirical Strategy – Hurricane Allison (2001)

Notes. This map illustrates our empirical strategy in the context of Hurricane Allison (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.

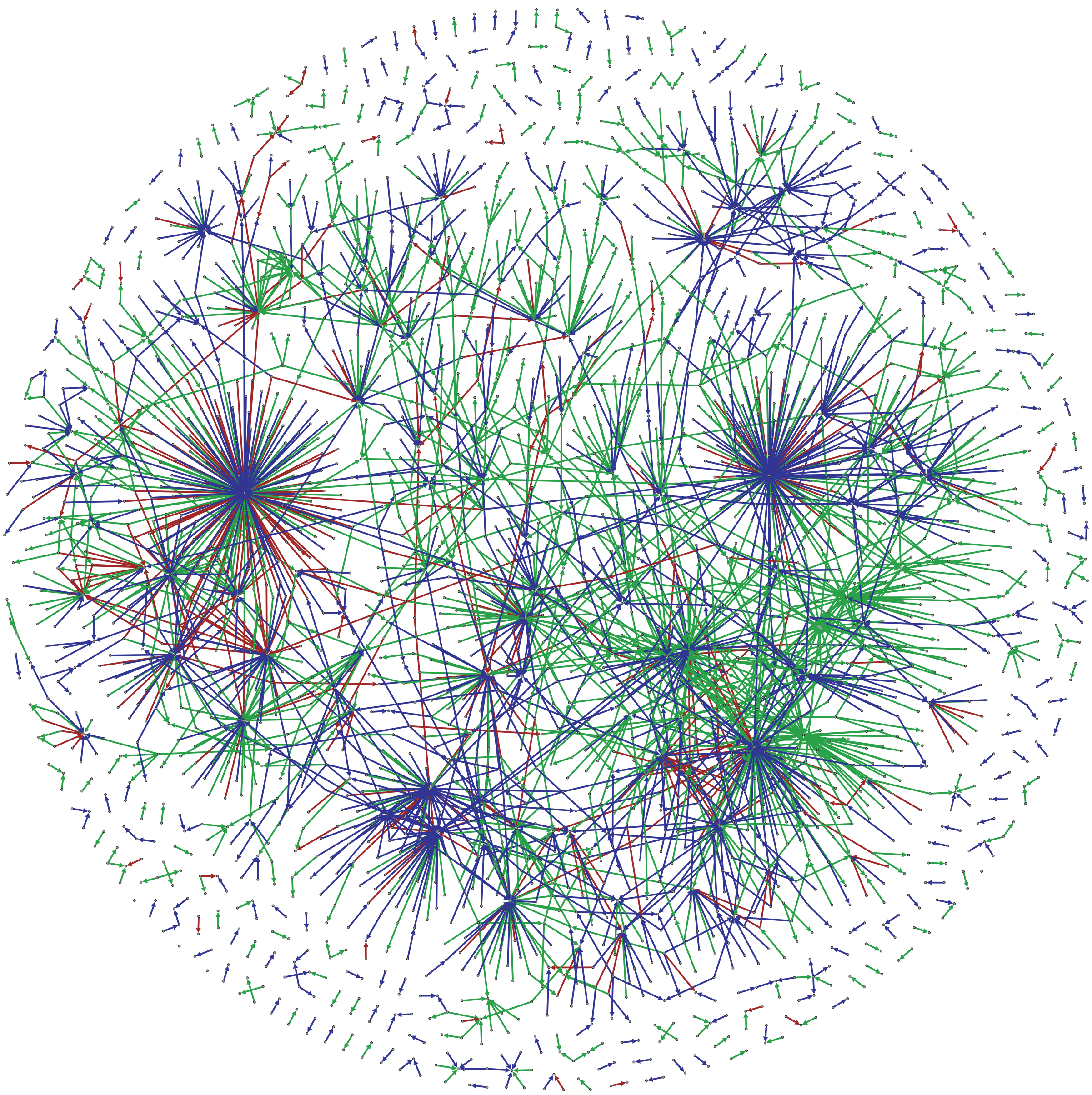

FIGURE IV

Network Evolution from 1995 to 2000

Notes. This figure illustrates the evolution of the supplier-customer network from 1995 to 2000. Relationships that were active in 1995 but not in 2000 are depicted in red. Relationships that are active in both years are depicted in green. Relationships that were not active in 1995 but were active in 2000 are depicted in blue.

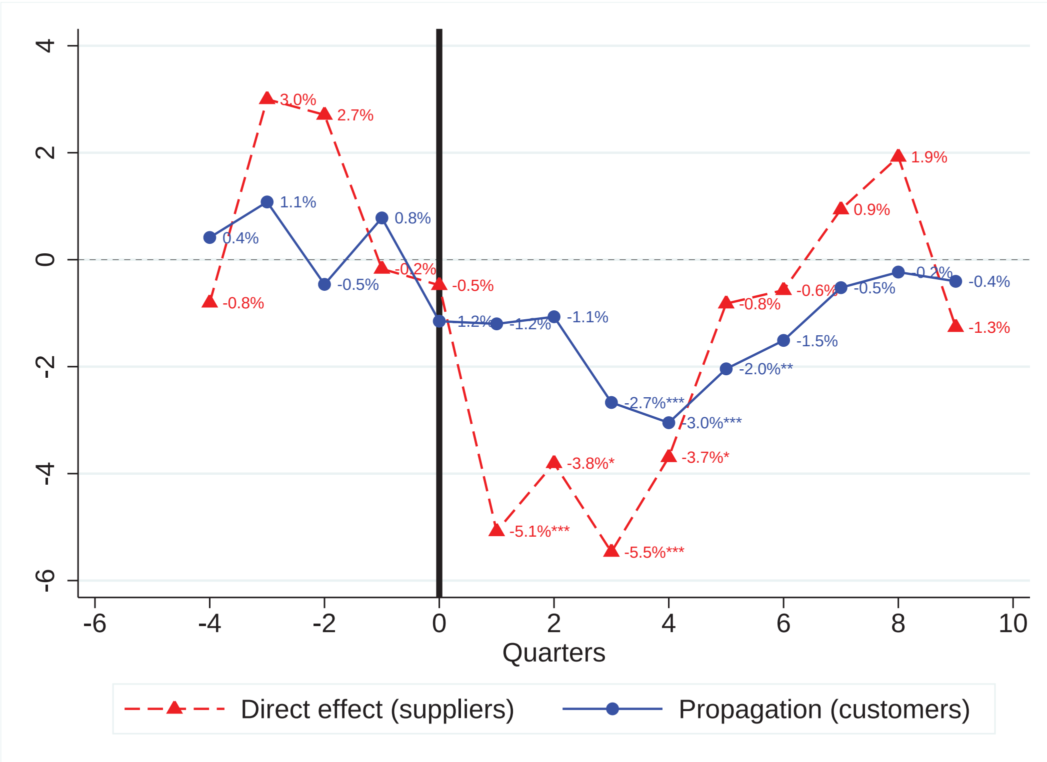

FIGURE V

Natural Disaster Strikes and Sales Growth

Notes. This figure presents difference-in-differences estimates of quarterly sales growth in the year before and the two years after 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 previous year. The red dashed line connects estimated coefficients, β_τ, of the following regression performed in the supplier sample:

$$\Delta Sales_{i,t-4,t} = \alpha + \sum_{\tau=-4}^{9} \beta_\tau . HitsFirm_{i,t-\tau} + \eta_i + \pi_t + \epsilon_{i,t}$$

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

$$\Delta Sales_{i,t-4,t} = \alpha + \sum_{\tau=-4}^{9} \beta_\tau . HitsFirm_{i,t-\tau} + \sum_{\tau=-4}^{9} \gamma_\tau . HitsSupplier_{i,t-\tau} + \eta_i + \pi_t + \epsilon_{i,t},$$

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 *** denote significance at the 10%, 5%, and 1%, respectively. The sample period spans 1978 to 2013.

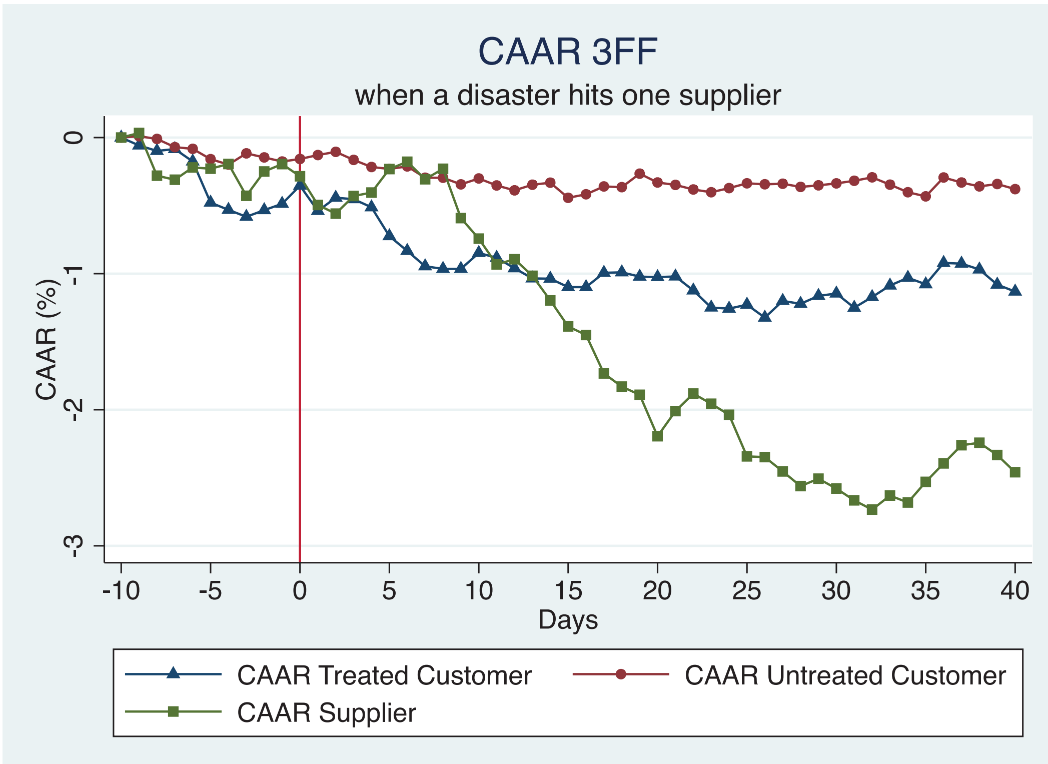

FIGURE VI
Cumulative Average Abnormal Returns

Notes. 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 three-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. We find 1,082 customer firm-disaster pairs satisfying these requirements.

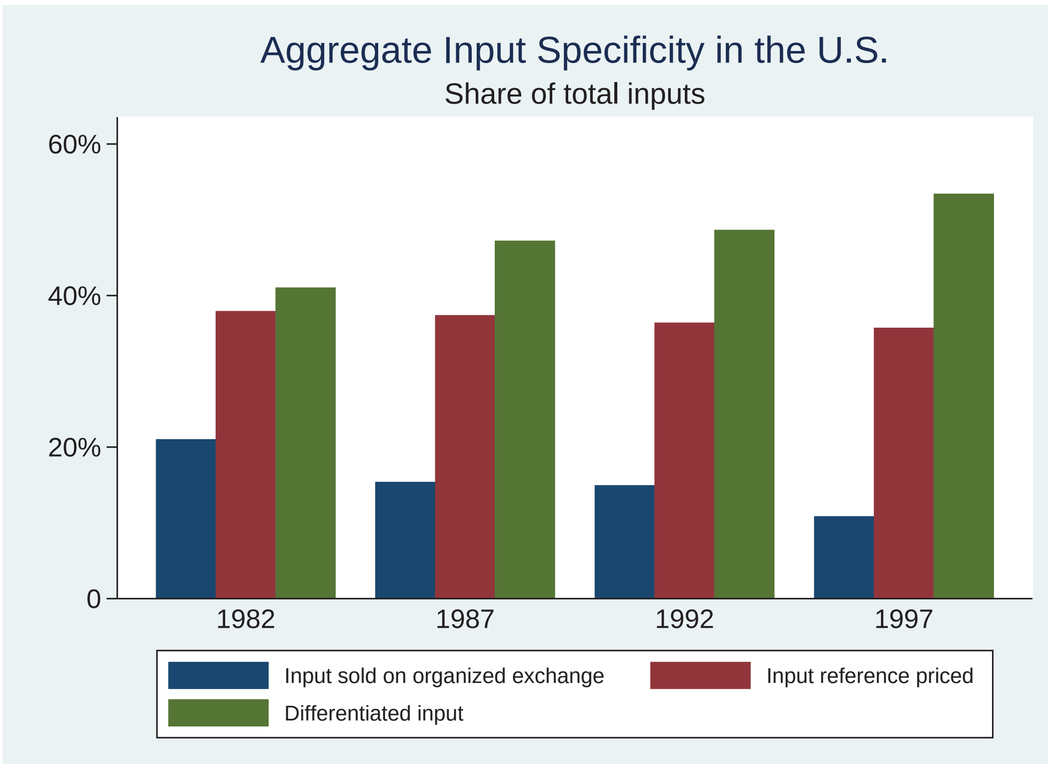

FIGURE VII
Aggregate Input Specificity in the U.S.

Notes. 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 that are reference priced in a trade publication, and those that are differentiated.