INTRODUCTION

Negative economic shocks have been found to propagate through input-output linkages to both upstream and downstream firms, leading to a substantial effect on the entire economy (Acemoglu et al., 2012; Bigio & La'O, 2016; Caliendo et al., 2014; di Giovanni & Levchenko, 2010). Suppliers of a firm directly affected by a negative shock due to natural disasters may also be indirectly affected because of lack of demand, whereas its customers may be affected because of lack of material, parts, and components. While the literature mostly relies on input-output tables aggregated at the sector...
level, recent studies have begun utilizing newly available firm-level data with information on supply-chain links to investigate this issue (Barrot & Sauvagnat, 2016; Carvalho et al., 2016; Lu et al., 2017).

Many of these studies take the Great East Japan Earthquake as a source of exogenous economic shocks because its direct effects are exogenous and extensive (Cavallo et al., 2010) and because it is one of the disasters that shed lights on supply chain disruptions caused by natural disasters. Another study by Boehm et al. (2015), who examine propagation from parent firms damaged by a disaster affecting their overseas affiliates, also focuses on the Great East Japan Earthquake. These studies confirm that, through supply chains, economic shocks by natural disasters can degrade the performance of firms that are located outside the directly affected region and even outside the country. However, the case of the Great East Japan Earthquake is unique in several aspects. First, it is one of the most devastating disasters in the world in decades. Second, Japanese supply chains have special characteristics, often described as keiretsu supply chains, which are constructed based on close and exclusive vertical relationships among firms. Those strong relationships may affect the resilience of supply chains. Because of those characteristics, there is a room to discuss the external validity of the evidence from the Great East Japan Earthquake case. One exception is the study by Barrot and Sauvagnat (2016), which examines all kinds of disasters in the United States, including earthquakes, blizzards, floods, and hurricanes, as a source of exogenous shocks, and finds there is the propagation of shocks through supply chains.

To add another case of disasters to the limited body of evidence, we take Hurricane Sandy (henceforth, the hurricane) that hit the east coast of the United States in October 2012 as a source of negative shocks to investigate how negative shocks from a hurricane propagate both within and across countries through supply chains. The hurricane is reported to have caused an economic loss of US$ 50 billion, the second largest economic loss from a natural disaster worldwide since 2010 (Center for Research on the Epidemiology of Disasters, 2017). The hurricane caused power outages, as is often the case with major disasters. It lasted for several days to 2 weeks, which is shorter than the cases of other United States major hurricanes, such as Katrina and Rita. In the case of the Great East Japan Earthquake, it took several days to 8 days for most of the areas to recover from the power outages.

Specifically, we estimate how much the sales of firms outside the hurricane’s disaster area changed after the hurricane if their direct or indirect customers or suppliers were located in the disaster-hit counties. We use ordinary least squares (OLS) estimation because of the exogenous nature of the hurricane, finding that after the hurricane, the sales growth of U.S. suppliers and customers of firms directly damaged by the hurricane was significantly lower than that of other firms. This finding confirms the upstream and downstream propagation within the country at the firm-level found in Barrot and Sauvagnat (2016) and Carvalho et al. (2016). We also confirm the finding of Barrot and Sauvagnat (2016) that input specificity results in difficulties of substitution for damaged supply-chain partners and thus, magnifies propagation. We further examine how characteristics of supply chains as a network affect propagation, because recent literature finds a large role of the structure of interfirm networks in propagation (Acemoglu et al., 2015b; Elliott et al., 2014; Joya & Rougier, 2019). Our analysis reveals that when a firm’s partners are densely connected with each other through supply chains, propagation of negative effects is augmented as the shock can circulate in the dense network.

This study contributes in various aspects to the growing literature on the propagation of economic shocks through supply chains (Acemoglu et al., 2015a; Auer et al., 2019; Barrot & Sauvagnat, 2016; Boehm et al., 2015; Caliendo & Parro, 2014; Caliendo et al., 2017; Carvalho et al., 2016; Cravino & Levchenko, 2016; Fieler & Harrison, 2018; di Giovanni et al., 2018; Horvath, 1998; Huo et al., 2019; Kikkawa et al., 2017; Long & Plosser, 1983; Tintelnot et al., 2018). First, our result that the hurricane shocks propagate substantially through supply chains adds to the external validity of the findings from the previous literature that investigate impacts of disasters (Barrot & Sauvagnat, 2016; Boehm
et al., 2015; Carvalho et al., 2016). Second, we find that input specificity and difficulties of substituting for damaged partners affect the degree of the propagation of shocks and confirm the role of search barriers in the propagation of shocks discussed in recent literature (Barrot & Sauvagnat, 2016). Third, we investigate how the network structure, network density, in particular, affects propagation rather than simply focusing on direct links with damaged firms. The use of measures of network structure is new in the empirical literature on the propagation of disaster shocks through supply chains, although a similar issue has been examined in the context of financial networks (Acemoglu et al., 2015; Barrot & van Marrewijk, 2019; Elliott et al., 2014). These findings add to the several strands of literature related to the capability of substituting for damaged firms or production network formation (Huneeus, 2018; Lim, 2017; Oberfield, 2018; Pankratz & Schiller, 2019).

In addition, this study, exploring disaster impact on production activities in and outside the disaster-hit region, relates to the literature on macroeconomic consequences of disasters. In the literature, some studies found a negative macroeconomic effect of natural disasters (Cavallo et al., 2013; Hsiang & Jina, 2014; Noy, 2009; Noy & Nualsri, 2007; Raddatz, 2009; Skidmore & Toya, 2002; Strobl, 2012), while some others found no significant or even positive effect (Albala-Bertrand, 1993; Fomby et al., 2013; Jaramillo, 2009; Loayza et al., 2012; Sawada et al., 2011; Skidmore & Toya, 2002). These mixed results may partly come from the heterogeneity of supply-chain characteristics that leads to different degrees of economic impacts, as found in this study. Different types of disasters may also affect supply chains differently. The literature on macroeconomic consequences across disaster types suggest that climatic disasters are associated with better recovery than geologic disasters, such as earthquakes (Sawada et al., 2011; Skidmore & Toya, 2002).

Finally, our findings suggest a policy implication that diversifying supply-chain partners can mitigate the propagation of shocks through supply chains and thus, lead to economic resilience. Although some studies argue the policy implications of the role of supply chains in recovery from disasters (Todo et al., 2015), better supply-chain structures to mitigate the propagation of disaster shocks have not been proposed in the literature. A Supporting Information Appendix is available online.

2 | EMPIRICAL STRATEGY

2.1 | Conceptual framework

Our conceptual framework is built upon general equilibrium models of production networks developed and extended by Acemoglu et al. (2012), Barrot and Sauvagnat (2016), and Carvalho et al. (2016). We particularly rely on Barrot and Sauvagnat (2016) and Carvalho et al. (2016), who examine the propagation of shocks from natural disasters, generating several theoretical predictions, as follows.

First, in the model of Barrot and Sauvagnat (2016), firms monopolistically produce a variety of goods that can be consumed or used as inputs for other products. A firm's production function is characterized by constant elasticity of substitution among labor and a variety of intermediate inputs and constant returns to scale. Simulation analysis by Barrot and Sauvagnat (2016) shows that the destruction of a firm's production capacity by a disaster negatively affects the output of its direct customers through input-output linkages. Using a similar theoretical model, Carvalho et al. (2016) reach the same conclusion. In their model, when a firm's productivity is negatively affected by a shock, the price of the firm's product becomes higher. As a result, its customers utilize a smaller amount of its product as an intermediate good, producing a smaller amount of their products. Indirect customers of the firm directly damaged by a shock, such as customers of their direct customers, or two-step customers, are also negatively affected, although the effect on indirect customers is smaller than the effect on direct
customers. These findings suggest the following testable hypotheses regarding the downstream propagation of a shock generated by a natural disaster through supply chains from suppliers to customers.

**Hypothesis 1** The sales growth of customers of firms directly damaged by a natural disaster is on average lower than that of customers of undamaged firms as a result of supply chain disruptions.

**Hypothesis 2** The sales growth of two-step customers of firms directly damaged by a natural disaster is on average lower than that of two-step customers of undamaged firms, and the effect on their two-step customers is smaller than the effect on their direct customers.

Second, Carvalho et al. (2016) further show that a negative productivity shock on a firm decreases the output of the firm’s upstream suppliers when labor and intermediates are substitutes. This effect is due to an increase in the demand for labor relative to intermediates because of a negative productivity shock on the intermediate-goods sector. As in the case of downstream propagation, negative shocks propagate further to more upstream suppliers beyond direct suppliers, although the propagation effect diminishes along supply chains. These findings lead to the following hypotheses regarding upstream propagation.

**Hypothesis 3** The sales growth of suppliers of firms directly damaged by a natural disaster is on average lower than that of suppliers of undamaged firms as a result of supply chain disruptions.

**Hypothesis 4** The sales growth of two-step suppliers, that is, suppliers of suppliers, of firms damaged directly by a natural disaster is on average lower than that of two-step suppliers of undamaged firms, and the effect on their two-step suppliers is smaller than the effect on direct suppliers.

These hypotheses have already been supported empirically by Barrot and Sauvagnat (2016) and Carvalho et al. (2016) using data for supply chains within a country. The present study extends their analysis to incorporate global supply chains. One possible cause of the difference is related to the difficulty of finding substitutes for damaged suppliers and customers. Barrot and Sauvagnat (2016) find, both theoretically and empirically, that shocks propagate more through supply chains when inputs are more specific and substitution is more difficult. Recently, theoretical and empirical analyses by Allen (2014), Antras et al. (2017), and Bernard et al. (2019) incorporate costs of searching for transaction partners and find that the search cost is an important determinant of partners. In our context, their results imply that when a firm’s suppliers or customers are affected by a negative shock, the firm can substitute new partners for damaged ones only if the expected benefit from having new partners exceeds the search cost.

Under these circumstances, substitution of suppliers and customers within a country may or might not be more difficult than substitution across countries. On the one hand, internationalized firms using a wide variety of inputs, including those from foreign countries, may have greater ability to collect information in the world market than firms with only domestic partners. Therefore, internationalized firms’ costs of searching for new partners are lower than those of non-internationalized firms. In addition, as internationalized firms are likely to be more productive, as argued by the heterogeneous-firm trade model of Melitz (2003) and evidenced by many empirical studies, such as Bernard and Jensen (2004), internationalized firms can obtain larger benefits from continuing production by finding new partners and thus, are willing to pay search costs. Therefore, internationalized firms may find it easier to substitute for inputs from firms affected by a shock. If this is the case, international propagation of shocks is smaller in size than intra-national propagation. On the other hand, inputs from a foreign country may be more specific to the exporting country and unavailable domestically. If so,
international substitution for inputs is more difficult than intra-national, and thus, shocks propagate more across countries than within a country.

Finally, we investigate the role of network density in the propagation of shocks. The egocentric network of a particular firm is considered to be dense when partners linked with the firm are also linked with each other. Theoretically, there are two conflicting views of the effect of network density on propagation. On the one hand, in a dense network, shocks are circulated and thus, may be amplified. In the context of diffusion of behaviors, Centola (2010) empirically finds quicker diffusion in dense networks than sparse ones. On the other hand, in a dense network, individuals and firms are more likely to trust each other, creating social capital (Coleman, 1988). In this situation, firms in dense supply chains may help each other absorb shocks in the wake of a disaster. Such dense supply chains are typically found in the keiretsu relationship among Japanese firms, where each large final assembler and its direct and indirect suppliers form an exclusive group of firms (Ahmadjian & Lincoln, 2001; Aoki, 1988). After the Great East Japan Earthquake in 2011, damaged firms involved in the keiretsu supply chains are found to more quickly recover from the disaster (Todo et al., 2015).

In practice, network density’s two opposing forces lead to mixed results regarding its effect on propagation both theoretically and empirically. For example, Acemoglu, Ozdaglar, et al. (2015) use a theory of interbank networks and find that dense networks are resilient to a sufficiently small financial shock because the shock is absorbed. However, they find that when a shock is sufficiently large, dense networks are not resilient because the shock cannot be absorbed but is instead circulated and amplified. In the literature on the effect of research collaboration networks on knowledge diffusion, several studies, such as Rost (2011) and Gilsing et al. (2008), find an inverted U-shaped relationship between network density and diffusion.

2.2 | Estimation methodology

To test these hypotheses, we consider the following estimation equation:

$$SalesGrowth_{i(2011-2012)} = \beta_0 + \beta_1 ShockXUS_i + \beta_2 ShockXnonUS_i + \beta_3 X_{i2011} + \epsilon_{i2012}. \tag{1}$$

The dependent variable, SalesGrowth$_{i(2011-2012)}$, is the growth rate of sales of firm $i$ from 2011 to 2012. Firm $i$ can be either in the United States but outside the disaster area or in any other country in the world.

Shock, or more precisely ShockXUS and ShockXnonUS, is a vector of key independent variables that represent ties with suppliers and customers directly hit by Hurricane Sandy. When we examine downstream propagation, that is, propagation from suppliers to customers, we measure ties with directly damaged suppliers using the dummy for the existence of damaged suppliers of firm $i$, following the previous studies (Barrot & Sauvagnat, 2016; Carvalho et al., 2016). In addition to firm $i$'s direct ties, Shock includes measures of suppliers of firm $i$'s suppliers, or firm $i$'s two-step suppliers, that were directly hit by the hurricane. To distinguish between propagation within the United States and beyond the United States, we classify Shock variables by the location of firm $i$, either in the United States or outside the United States, using the interaction terms between U.S. or non-U.S. dummy and Shock variables. Similarly, when we examine upstream propagation from customers to suppliers, we use the dummy variables for firm $i$’s damaged customers and damaged two-step customers. The vector of the control variables $X$ includes firm attributes and network-related variables, as described in Subsection 3.2.

To estimate Equation (1), we use OLS estimations, following Barrot and Sauvagnat (2016) and Carvalho et al. (2016). This simple method is appropriate in the present case because Hurricane Sandy
is an exogenous shock, and therefore, whether a firm is linked to damaged firms should be exogenously determined, after controlling for the total number of links of the focal firm. We check the exogeneity of the shock by testing the correlation between the shock and pre-disaster sales growth, as shown in Subsection 4.2.

3 | DATA

3.1 | Data sources

This study uses two datasets, LiveData of FactSet Revere and Osiris of Bureau van Dijk. LiveData is a unique firm-level dataset that covers some 110,000 major firms from around the world, including 17,656 in the United States (US), and contains information on supply-chain ties among them, which is collected from public sources, such as financial reports, firm websites, and news articles. Supply-chain information has become widely available through the Internet. Most importantly, in the United States, the Financial Accounting Standards Board requires publicly listed firms to disclose customers who account for at least 10% of total sales, including foreign customers, in their financial reports. After automatically collecting information from the Internet and identifying the identification number of each supplier and customer, trained analysts of FactSet Revere manually verify it. Therefore, the coverage of supply-chain information in LiveData is sufficiently high, at least as high as that in Compustat, which also relies on information from U.S. financial reports and has been used in previous studies, such as Barrot and Sauvagnat (2016), as we will show later. Although LiveData focused on U.S. firms in earlier periods, it has recently expanded its coverage to other regions, mostly Europe and Asia. In this regard, an advantage of LiveData over Compustat is that the former includes more extensive supply-chain information of non-U.S. firms. We utilize LiveData for 2011, one year before Hurricane Sandy, to identify pre-disaster global supply chains, which include 110,316 firms and 71,669 supply chain ties. Among the 110,313 firms, 17,656 are located in the United States, 3,908 in Japan, and 2,499 in the United Kingdom (UK).

The other dataset, Osiris, includes firm-level data for mostly publicly listed firms in a number of countries. Because Osiris contains detailed and globally comparable financial information, we extract from Osiris each firm’s information such as sales, value of total assets, number of employees, firm age, industry code, and fiscal year end.

We merge LiveData and Osiris first using the International Securities Identification Number (ISIN), then using Ticker Symbols, countries, and company names for unmatched firms, and finally using zip codes, countries, and company names. Among 37,698 listed firms in Osiris, we have to omit from the sample for regressions 11,178 firms that cannot be matched with any firm in LiveData, although we construct network-related variables from the LiveData before the merge. We exclude firms in the financial and real estate industries and governments, assuming that those are less likely to be affected by supply chain disruptions caused by natural disasters. Our benchmark regressions restrict our sample to firms that were not directly hit by Hurricane Sandy to examine propagation from damaged firms only to firms that were not directly damaged by the hurricane. Therefore, we exclude 714 firms in areas damaged at least moderately, as defined by the Federal Emergency Management Agency (FEMA) (Federal Emergency Management Agency (FEMA), 2014) and shown as hatched areas in Figure 1. In addition, we limit the sample to those whose operation status is active as of 2012, dropping 21 inactive firms. Finally, we exclude firms without sufficient information. Accordingly, the number of observations for our benchmark regression is 11,697, among which 1,984 are in the United States, 2,487 in Japan, 2,050 in China,
946 in Taiwan, and 558 in the United Kingdom, as shown in Table 1. The same table presents the number of publicly listed firms in 2011 in each of the top five countries in our sample in column (4) and the ratio of firms in our sample (for the United States, we add the number of listed firms in the disaster areas that are dropped from the sample) to publicly listed firms in column (5), showing that the coverage for most countries is reasonably high.

Because of the coverage of LiveData and Osiris, our dataset mostly focuses on major transactions among publicly listed firms and relatively large firms in the world. For example, the average number of suppliers per firm in our dataset is approximately two, whereas the median number of employees of any firm's suppliers and customers is 2,196.5. However, it should be emphasized that our focus on major transactions of major firms is appropriate for the purpose of this study, because economic shocks are less likely to propagate from small to large firms or through transactions of a small amount.

Finally, it should be noted that our analysis is conducted at the firm level, not at the establishment level, because the locational information of establishments of firms is limited, and because we do not have any information about supply-chain relationships between establishments or sales of establishments. See Appendix A1 in supporting information for more details.
| Country        | Number of firms in the sample | Share in the sample (%) | Number of listed firms in the disaster areas dropped from the sample | Number of publicly listed firms in 2011 | (1 + 3)/(4) |
|---------------|-------------------------------|-------------------------|----------------------------------------------------------------|----------------------------------------|-------------|
| United States | 1,984                         | 16.96                   | 714                                                               | 4,171                                   | 0.647       |
| Japan         | 2,487                         | 21.26                   |                                                                   | 2,280                                   | 1.091       |
| China         | 2,050                         | 17.53                   |                                                                   | 2,342                                   | 0.875       |
| Taiwan        | 946                           | 8.09                    |                                                                   | 790                                     | 1.197       |
| United Kingdom| 558                           | 4.77                    |                                                                   | 1,987                                   | 0.281       |

Note: Data Source of column (4): CEIC (2020) for Taiwan and World Bank (2018) for others. In column (5), some are above 1, which is likely due to the difference in the timing of reflecting the information when firms are delisted.
3.2 | Variable construction

Our key independent variables are dummies for the existence of each firm's suppliers and customers that were directly damaged by Hurricane Sandy. To create these variables, we first identify the global supply chains in 2011, one year before Hurricane Sandy, using all firms in LiveData, including observations omitted from our estimation sample.

Next, we define firms directly damaged by Hurricane Sandy as 774 firms whose headquarters are in “very highly damaged counties,” according to the FEMA (2014). In these highly affected regions (filled-in areas surrounded by the hatched area in Figure 1), more than 10,000 people in each county were exposed to storm surge, many buildings were flooded more than one meter in-depth, and their exterior walls collapsed (Federal Emergency Management Agency, 2013; FEMA, 2014). It is most likely that the production activities of firms subjected to such conditions were heavily disturbed. We create a dummy variable coded one if any of each firm's suppliers is located in these heavily affected counties and another coded one if any of its two-step suppliers (suppliers of suppliers) is located in these counties. In addition, we define corresponding dummies for customers and two-step customers in the heavily affected counties.

To control for the size of the production network of each firm, we include the log of the number of suppliers, two-step suppliers, customers, two-step customers, suppliers of customers, and those transaction partners in the United States plus one in the set of independent variables. We also control for the internationalization of the focal firm, using the logs of the number of suppliers and customers in the country in which the focal firm is located plus one. We also incorporate another measure, Bonacich (1987)'s power centrality to represent each firm's centrality in the global supply chain. Although the number of supply chain partners is also a measure of network centrality, it captures only direct links and ignores indirect links or the network characteristics of partners. Bonacich (1987)'s power centrality of \( u, c_u(\alpha, \beta) \) is defined as
\[
\sum_v \alpha + \beta c_v A_{uv},
\]
where \( \beta \) and \( A \) are an attenuation parameter, and the graph adjacency matrix. \( \alpha \) is set such that \( \sum_u c_u(\alpha, \beta)^2 \) equals the number of vertices. Bonacich (1987)'s power centrality is designed to evaluate the bargaining power, incorporating the aspect that the partner firms with more links have more power in negotiation as they have more options.

In some specifications, we incorporate the density of firms' egocentric networks, measured by the local clustering coefficient. The density of ego network is defined as the ratio of the number of actual supply-chain ties between partners of the focal firm to the number of all possible ties between them (Barabási, 2016; Jackson, 2010). For example, if a firm has three partners and two among the three are also connected with supply chains, its density is one-third. When a firm is not linked with any other firm or linked with only one firm, we define the density as zero. In the estimations, we also include dummy variables for no link and one link to account for any possible bias due to the arbitrary definitions.

The dependent variable is sales growth from 2011 to 2012. Sales growth is calculated as
\[
\text{SalesGrowth}_{i}^{\text{2011-2012}} = 2 \times \frac{(\text{netsales}_{2012} - \text{netsales}_{2011})}{(\text{netsales}_{2012} + \text{netsales}_{2011})}.
\]
This is the form recommended by Cravino and Levchenko (2016) and Davis et al. (1996). The denominator is the average sales of the two periods, not the pre-disaster sales. Some of the attractive features of this form are that it can be calculated for observations whose values at the start or end period are zero and are bounded between -2 and 2. Control variables include sales growth from 2010 to 2011 to capture the pre-disaster characteristics, sales per worker in 2011 in log form to represent productivity, and the number of workers and value of total assets in 2011 in log form to represent firm size, firm age, interaction terms between industry dummies and country dummies for firms outside the United States, and those between industry dummies and state dummies for firms in the United States. These interaction terms with industry dummies help us to control price changes at the level of industry-country.
pairs for non-US firms and industry-state pairs for U.S. firms. The single terms of each interaction term are also included. The dependent variable and these controls are constructed based on Osiris data. We use industry dummies based on the firms’ four-digit industry group codes in the Global Industry Classification Standard (GICS). Country dummies are classified by the location of the firm headquarters.

The end month of the fiscal year reported in Osiris varies across countries and firms, although it is December for the majority, or 64 percent, of firms (See Appendix A2 and Appendix Table A1 in supporting information for more details). Because sales of each firm in our sample cover different time periods depending on its fiscal year end, the effect of supply-chain ties with directly affected firms on sales growth should also be affected by the fiscal year end. Therefore, for all the regressions throughout the paper, we include dummies for different fiscal-year end months and interaction terms between these dummies and the key variables for supply-chain ties, setting December as the base month. That is, our actual estimation equation is given by:

\[
SalesGrowth_{i(2011-2012)} = \beta_0 + \beta_1 \text{ShockXUS}_i + \beta_2 \text{ShockXnonUS}_i + \sum_{k=1}^{11} \gamma_{1k} D_{ik} \times \text{ShockXUS}_i \nonumber \\
+ \sum_{k=1}^{11} \gamma_{2k} D_{ik} \times \text{ShockXnonUS}_i \nonumber \\
+ \sum_{k=1}^{11} \gamma_{3k} D_{ik} + \beta_3 X_{2011} + \epsilon_{i2012},
\]

where \( \text{ShockXUS} \) and \( \text{ShockXnonUS} \) are the vector of key independent variables as explained in Equation (1), that is, ties with suppliers and customers directly hit by Hurricane Sandy for U.S. firms and non-U.S. firms, respectively, and \( D_{ik} \) is the dummy variable that takes a value of one if firm \( i \)'s fiscal year end month is month \( k \).

### 3.3 Descriptive statistics

The upper rows of Table 2 show the summary statistics for the variables related to supply chains. The mean and median of the number of suppliers are 1.618 and 0, respectively. On average, the number of domestic suppliers in our data is 0.784, indicating that the number of domestic suppliers and that of foreign suppliers do not differ substantially. Focusing on U.S. firms, we find that their average number of domestic suppliers is 3.917.\(^1\)

Looking at the mean of the dummy variable for damaged suppliers, we find 3.9% of all firms in our global sample are directly connected to suppliers directly damaged by the hurricane. When we disaggregate the dummy for any link with damaged suppliers into a dummy for U.S. firms and non-US firms, 2.7% of U.S. firms are directly linked to suppliers in the damaged area.

The mean of the number of customers is 2.083. The mean of the number of domestic customers for the global sample and the U.S. sample is 0.805 and 3.802,\(^2\) respectively. Including indirect links, firms in the sample have on average 24 two-step customers, although it should be emphasized that this relatively large number is mostly due to the fat-tailed distribution with a maximum of 2,297. Furthermore, 2.9% of U.S. firms have customers in the damaged areas, while the corresponding figure for non-US firms are 1.2%.
### TABLE 2  Summary statistics

| Variable                                      | Mean  | SD    | Min. | Median | Max  |
|-----------------------------------------------|-------|-------|------|--------|------|
| **Links with suppliers in 2011**             |       |       |      |        |      |
| # of suppliers                                | 1.618 | 7.755 | 0    | 0      | 233  |
| -- in logs                                    | 0.363 | 0.774 | 0    | 0      | 5.455|
| # of domestic suppliers                       | 0.784 | 4.993 | 0    | 0      | 189  |
| -- in logs                                    | 0.201 | 0.567 | 0    | 0      | 5.247|
| # of U.S. suppliers                           | 0.817 | 5.089 | 0    | 0      | 189  |
| -- in logs                                    | 0.202 | 0.581 | 0    | 0      | 5.247|
| # of suppliers in two steps                   | 19.520| 86.432| 0    | 0      | 1,341|
| -- in logs                                    | 0.659 | 1.523 | 0    | 0      | 7.202|
| **Links with damaged suppliers in 2011**      |       |       |      |        |      |
| Dummy for any link with damaged suppliers × U.S. dummy | 0.027 | 0.162 | 0    | 0      | 1    |
| Dummy for any link with damaged suppliers × non-U.S. dummy | 0.012 | 0.108 | 0    | 0      | 1    |
| Dummy for any 2-step link with damaged suppliers × U.S. dummy | 0.064 | 0.244 | 0    | 0      | 1    |
| Dummy for any 2-step link with damaged suppliers × non-US dummy | 0.043 | 0.203 | 0    | 0      | 1    |
| **Links with customers in 2011**              |       |       |      |        |      |
| # of customers                                | 2.083 | 7.200 | 0    | 0      | 196  |
| -- in logs                                    | 0.424 | 0.885 | 0    | 0      | 5.283|
| # of domestic customers                       | 0.805 | 3.408 | 0    | 0      | 107  |
| -- in logs                                    | 0.232 | 0.608 | 0    | 0      | 4.682|
| # of U.S. customers                           | 0.812 | 3.511 | 0    | 0      | 107  |
| -- in logs                                    | 0.222 | 0.612 | 0    | 0      | 4.682|

(Continues)
| Variable | Mean | SD  | Min. | Median | Max  |
|----------|------|-----|------|--------|------|
| # of customers in two steps | 23.775 | 101.468 | 0 | 0 | 2,297 |
| -- in logs | 0.762 | 1.644 | 0 | 0 | 7.740 |
| Links with damaged customers in 2011 | | | | | |
| Dummy for any link with damaged customers × U.S. dummy | 0.029 | 0.168 | 0 | 0 | 1 |
| Dummy for any link with damaged customers × non-U.S. dummy | 0.012 | 0.109 | 0 | 0 | 1 |
| Dummy for any 2-step link with damaged customers × U.S. dummy | 0.075 | 0.264 | 0 | 0 | 1 |
| Dummy for any 2-step link with damaged customers × non-US dummy | 0.045 | 0.208 | 0 | 0 | 1 |
| Other networks measure in 2011 | | | | | |
| Local Clustering Coefficient | 0.014 | 0.071 | 0 | 0 | 1 |
| Firm attributes | | | | | |
| Sales growth from 2010 to 2011 | 0.104 | 0.324 | −1.969 | 0.079 | 2.000 |
| Sales growth from 2011 to 2012 | 0.013 | 0.327 | −2.000 | 0.014 | 1.999 |
| Sales per worker in 2011 | 647 | 7,317 | 0 | 222 | 496,205 |
| -- in logs | 5.391 | 1.221 | −3.298 | 5.401 | 13.115 |
| # of workers in 2011 | 4,966 | 27,798 | 1 | 931 | 2,200,000 |
| -- in logs | 6,769 | 1.916 | 0 | 6,836 | 14,604 |
| Value of total assets in 2011 | 1,697,118 | 8,202,269 | 4 | 257,425 | 331,052,000 |
| -- in logs | 12,444 | 1.976 | 1.495 | 12,458 | 19.618 |
| Firm age | 32.787 | 30.815 | 2 | 22 | 647 |
The bottom rows of Table 2 indicate summary statistics of other network measures and other control variables. The median pre-disaster sales growth is 7.9%, whereas the median number of workers and firm age is 931 and 22 years, respectively. These figures confirm that the sample firms are mostly large, established, and growing firms.

Appendix Table A2 reports the share of each of the four-digit industries classified by the GICS, as explained in Subsection 3.2. The major industries in our sample are the capital goods, materials, and technology hardware and equipment industries.

4 | RESULTS

4.1 | Results for direct effects of disaster shocks

Before we explore the propagation of disaster shocks, we first test whether or not the sales growth of the firms whose headquarters are located in the counties that were hit by Hurricane Sandy is negatively affected. For this purpose, we use a sample different from the main sample explained above, or a sample of both U.S. firms in and outside the disaster-hit areas taken from the same data sources as the main sample, and regress the sales growth of firms on a dummy variable, indicating whether the firm was in the disaster-hit areas. In this estimation, we control for firms' characteristics, such as sales growth in the pre-disaster period, sales per worker in 2011 in log form, the number of workers in 2011 in log form, value of total assets in 2011 in log form, firm age, and interaction terms between industry dummies and state dummies.

The results are presented in Table 3. As shown in column (1), the coefficient of the disaster shock dummy is negative and significant. Such a negative effect of the shock dummy is not observed for alternative shock dummy that indicates whether the firm is in the counties with lower damage (column (2)), suggesting that the hurricane had a negative impact on the sales growth of the firms in counties that suffered “very highly” from the hurricane. In Appendix Table A3, we further find that the direct disaster shock is not significantly correlated with pre-disaster sales growth. These findings suggest that the hurricane had a negative impact on the sales growth of the firms in counties that suffered “very highly” from the hurricane, while these affected firms were not systematically different from others in the pre-disaster period.

4.2 | Balancing tests

For the remaining analysis, we use the baseline sample of firms that are not directly damaged by the hurricane as described in Section 3.1. Before getting into the main analysis, we test the exogeneity of shocks of the hurricane because our OLS estimations rely on this assumption. For this purpose, we run OLS estimations to examine whether a firm’s supply chain links to damaged suppliers or customers can predict sales growth before the disaster, including network variables, the interaction terms between country and industry dummies, and those between U.S.-state and industry dummies as control variables. Table 4 shows that neither the dummy for the existence of suppliers nor customers in disaster areas is correlated with sales growth before the hurricane. The results suggest that direct supply-chain links with damaged firms are randomly allocated to firms in our sample, and hence, our key variables of interest, the dummies for the existence of links with damaged firms, should be uncorrelated with the error term in Equation (2). Therefore, our use of OLS estimations is justified.
The benchmark results of the downstream propagation of disaster shocks are presented in Table 5. In all estimations, we include the interaction terms between each of the dummies for the end month of the accounting period and the key independent variables for links with damaged firms but do not present the results for the interaction terms for the brevity of presentation. Because the base case for the fiscal year end is December, the coefficient of the key independent variable represents the effect on the change rate of sales from the calendar year 2011 to calendar year 2012.

Columns (1) and (2) of Table 5 suggest that when U.S. firms are linked with any damaged supplier, their sales growth is 1.89 percentage points lower than when they are not directly linked with any damaged supplier. This result suggests that negative shocks of the hurricane propagated downstream along supply chains to U.S. customers and the propagation effect is not only statistically significant but also economically significant, supporting Hypothesis 1 in Subsection 2.1. In column (3) of Table 5, we consider the potential direct impact from other major disasters that hit the United States from 2010 to 2012 by including the dummy variable that indicates whether the firm’s headquarter is located in the counties hit by the other disasters during the period. Although Hurricane Sandy is much bigger than any other during the period, the other disasters may have had an influence on firms’ sales and biased the results. Following Barrot and Sauvagnat (2016), we obtain the list of disasters and county-level location information of each disaster from Spatial Hazard Events and Losses Database for the United States Version 18.1. As in column (3), the results are not affected even after considering the effect of other disasters.

Furthermore, in Table 5, we observe that the coefficients of the links with damaged suppliers for their non-U.S. customers (Dummy for any link with damaged suppliers × non-U.S. dummy) are positive but statistically insignificant, indicating no significant effect on non-U.S. customers.
evidence implies that the negative shock from the hurricane did not significantly propagate down-
stream beyond the U.S. borders.

Boehm et al. (2015) find the international propagation from Japanese parent firms to foreign af-
filiates in the wake of the Great East Japan Earthquake. The difference from their study probably
comes from two reasons. First, because the magnitude of the direct damages by the Great East Japan
Earthquake was substantially larger than that by Hurricane Sandy, the economic effect of the former
is more likely to propagate widely than that of the latter. Second, the difference in the results may
reflect the difference in flexibility of links between intra-firm and arms-length transactions. In intra-
firm transactions, inputs are more likely to be firm-specific and unavailable in the market. As a result,
propagation between unaffiliated firms has been found to differ from that between affiliated firms
according to some anecdotal evidence (Hattori, 2011).

In addition, the coefficients of indirect two-step links with damaged suppliers in columns (2) and
(3) of Table 5 are negative but insignificant for both U.S. and non-U.S. customers. This result does
not support Hypothesis 2, implying that there is no propagation of the negative shock from the hurri-
cane beyond direct customers. However, Hypothesis 2 also states that the effect on indirect customers
would be smaller than those on direct customers because negative shocks are absorbed along supply
chains due to the substitution of partner firms. Our results indicate that negative shocks substantially

| TABLE 4 | Balancing tests |
|----------|----------------|
|          | (1)            | (2)            | (3)            | (4)            |
| Dependent variable: Sales growth 2010–2011 |
| Dummy for any link with damaged suppliers × U.S. dummy | −0.0151 (0.0112) |
| Dummy for any link with damaged suppliers × non-U.S. dummy | 0.0110 (0.00711) |
| Dummy for any link with damaged customers × U.S. dummy | −0.0283 (0.0267) |
| Dummy for any link with damaged customers × non-U.S. dummy | 0.00327 (0.0196) |
| Network controls | Yes | Yes | Yes | Yes |
| Country dummies × Industry dummies | Yes | Yes | Yes | Yes |
| U.S.-state dummies × Industry dummies | Yes | Yes | Yes | Yes |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes | Yes | Yes |
| Observations | 11,697 | 11,697 | 11,697 | 11,697 |
| R² | .206 | .206 | .206 | .207 |

Notes: Robust standard errors clustered at the country level are in parentheses. Network controls include the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level; **statistical significance at 5% level; ***statistical significance at 1% level.
diminish along supply chains and disappear in two steps. Barrot and Sauvagnat (2016) also find no downstream propagation beyond direct customers based on firm-level panel analysis for the United States. Although Carvalho et al. (2016) find propagation beyond direct customers up to customers four steps away from damaged suppliers after the Great East Japan Earthquake, this is possible because of the extremely large direct effect of the Great East Japan Earthquake, as mentioned in the earlier paragraph of this section and Section 1. Another possible reason for the difference is that supply chains of Japanese firms are likely to be more vulnerable to economic shocks, because they are characterized by strong and long-term relationships known as keiretsu (Dyer & Nobeoka, 2000). In a keiretsu relationship, inputs are often developed through the collaboration between the supplier and the customer and thus, firm-specific or even product-specific (Aoki, 1988). Moreover, severing long-term relationships is more difficult (Altomonte & Ottaviano, 2009). The input-specific and long-term keiretsu relationships may have led to the propagation of the shock to indirectly linked supply-chain partners observed in Carvalho et al. (2016).

The results for upstream propagation from damaged customers to their suppliers in Table 6 suggest that upstream propagation is similar to downstream propagation. Table 6 shows negative, significant,

| TABLE 5 Effects of damaged suppliers |
|---------------------------------------|
| (1)                                   |
| Dummy for any link with damaged suppliers × U.S. dummy | −0.0189** |
|                                         | (0.00820) |
| Dummy for any link with damaged suppliers × non-U.S. dummy | 0.00837 |
|                                         | (0.0151) |
| Dummy for any 2-step link with damaged suppliers × U.S. dummy | −0.0222 |
|                                         | (0.0149) |
| Dummy for any 2-step link with damaged suppliers × non-U.S. dummy | −0.00932 |
|                                         | (0.0332) |
| Controls                               | Yes |
| Country dummies × Industry dummies     | Yes |
| U.S. state dummies × Industry dummies  | Yes |
| Dummies for the end month of the accounting period and their interaction with supply-chain shock variables | Yes |
| Other disaster dummy                   | No |
| Observations                           | 11,697 |
| R²                                    | .186 |

Notes: Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich’s power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level;
**statistical significance at 5% level;
***statistical significance at 1% level.
and large effects of the existence of links with damaged customers on sales growth of U.S. suppliers, which is consistent with Hypothesis 3. If a firm with no link with damaged customers were linked with a damaged customer, its sales growth rate would decline by 5.15 percentage points because of the propagation of negative shocks. This finding suggests that domestic suppliers of directly damaged firms are affected by a lack of demand from damaged customers immediately after the hurricane.

It is notable that the effect of damaged firms on their supply-chain partners (Tables 5 and 6) is smaller than the effect of the hurricane on damaged firms (Table 4), confirming that the indirect effect is smaller than the direct effect. In addition, the impact of damaged suppliers on their U.S. customers (Table 5) is smaller than the impact of damaged customers on their U.S. suppliers (Table 6). The difference in the size of the effect between upstream and downstream propagation may imply that suppliers can be replaced by another relatively easily, while customer firms are not. Accordingly, downstream propagation from suppliers to customers can be mitigated more than upstream propagation from customers to suppliers. The importance of supplier substitution is in line with the findings in previous studies such as Barrot and Sauvagnat (2016).

### TABLE 6  Effects of damaged customers

|                          | (1)             | (2)             | (3)             |
|--------------------------|-----------------|-----------------|-----------------|
| **Dependent variable:**  | **Sales growth 2011–2012** |
| Dummy for any link with damaged customers × U.S. dummy | $-0.0515^{***}$ | $-0.0471^{***}$ | $-0.0476^{***}$ |
|                          | (0.0153)        | (0.00739)       | (0.00731)       |
| Dummy for any link with damaged customers × non-U.S. dummy | 0.0211          | 0.0194          | 0.0195          |
|                          | (0.0355)        | (0.0375)        | (0.0375)        |
| Dummy for any 2-step link with damaged customers × U.S. dummy | $-0.0144$       | $-0.0143$       |                 |
|                          | (0.0189)        | (0.0189)        |                 |
| Dummy for any 2-step link with damaged customers × non-U.S. dummy | $-0.0218$       | $-0.0219$       |                 |
|                          | (0.0229)        | (0.0230)        |                 |
| **Controls**             | Yes             | Yes             | Yes             |
| Country dummies × Industry dummies | Yes             | Yes             |                 |
| U.S. state dummies × Industry dummies | Yes             | Yes             |                 |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes             | Yes             |                 |
| **Other disaster dummy** | No              | No              | Yes             |
| **Observations**         | 11,697          | 11,697          | 11,697          |
| **$R^2$**                | .186            | .189            | .189            |

**Notes:** Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich’s power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level;
**statistical significance at 5% level;
***statistical significance at 1% level.
In contrast, we do not find any significant effect of links with damaged customers on non-US suppliers in Table 6, as in the case of the effect of links with damaged suppliers in Table 5. This result suggests that negative shocks did not propagate significantly from damaged customers in the United States to their suppliers outside the United States.

Last, two-step links with damaged customers have an insignificant effect on U.S. and non-US suppliers (columns [2] and [3], respectively, of Table 6), partly supporting Hypothesis 4. Therefore, we conclude that damaged customers did not negatively and substantially affect their indirect suppliers.

4.4 Robustness checks

To check the robustness of the benchmark results, we experiment with several alternative specifications. First, the benchmark estimations define firms directly damaged by the hurricane as those in “very highly damaged areas” identified by FEMA (2014) (Figure 1). However, in these “very highly damaged areas,” there must have been a variation in the level of damages across firms and households. If this is the case, some of the firms defined as damaged in our data were not heavily damaged, and accordingly, the effect of links with “damaged firms” in our data underestimates the effect of links with truly damaged firms.

To identify links with truly damaged firms, we assume that when a firm is extremely damaged and thus, could not recover or needed a very long time to recover, supply-chain links with the firm should have been lost after the hurricane. Therefore, we alternatively define links with damaged firms as those that existed in the pre-disaster supply-chain link data but did not exist anymore in the post-disaster data. Then, we conduct OLS estimations as before, using the alternatively defined dummy variable for links with damaged firms and report the results in Table 7. Columns (1) and (2) indicate that the effect of direct suppliers and customers which suffered from the disaster on sales growth of U.S. firms is negative and significant, while their effect on firms outside the United States is insignificant. These are consistent with the benchmark results, confirming propagation within the country but no significant propagation beyond the country.

Second, in the benchmark regressions, firms in the disaster-hit areas are defined as those whose headquarter is located in the very highly damaged counties officially defined. Alternatively, we utilize the address information of establishments of firms reported for a subset of firms and define a firm in the disaster-hit areas if any establishment of the firm is located in the very highly damaged counties (See Appendix A1 in supporting information for more details). The results shown in Table 8 are essentially the same as the benchmark results.

Third, although we have used dummy variables for the various types of supply-chain links as the key independent variables in our estimations, the effect of supply chain links with damaged suppliers/customers may be increasing with the number of such suppliers/customers. Therefore, we experiment with the log of the number of suppliers or customers of various types examined in the benchmark estimations. We have obtained similar results with the baseline, as shown in Appendix Table A4 for brevity.

Finally, because our data cover major supply-chain links between major firms in the world, the number of suppliers and customers reported in the data is small and the median is zero (Subsection 3.3). To check whether the presence of many firms with only a few reported suppliers or customers biases our results, we add interaction terms between the key variables and the dummy for zero or one supplier or customer. The results in Appendix Table A5 indicate that the effect of links with damaged suppliers and customers is significant only for firms with more than one reported links, possibly because their supply-chain links are more adequately captured in the data than those with one or zero links.
We confirm the exogeneity of the negative shock from the hurricane using the balancing tests for sales growth in the pre-disaster period, as shown in Table 4. However, we are still concerned about whether our results are generated by the peculiar characteristics of damaged firms because the hurricane hit the industrial areas on the east coast of the United States around New York City. To check whether this is the case, we experiment with two sets of placebo tests. First, we estimate the effect of supply-chain links with firms that are not in the damaged areas of the hurricane but are similar in attributes to those in the damaged areas. We select these firms similar to damaged firms from all U.S. firms not directly damaged by the hurricane using a propensity score matching (PSM) technique. That is, we estimate how the dummy variable for damaged firms is correlated with the number of workers, amount of total assets, and industry dummies using logit and match each damaged firm with another with the closest predicted probability. Second, we estimate the effect of links with firms in neighboring states of the U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich's power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

### Placebo tests

We confirm the exogeneity of the negative shock from the hurricane using the balancing tests for sales growth in the pre-disaster period, as shown in Table 4. However, we are still concerned about whether our results are generated by the peculiar characteristics of damaged firms because the hurricane hit the industrial areas on the east coast of the United States around New York City. To check whether this is the case, we experiment with two sets of placebo tests. First, we estimate the effect of supply-chain links with firms that are not in the damaged areas of the hurricane but are similar in attributes to those in the damaged areas. We select these firms similar to damaged firms from all U.S. firms not directly damaged by the hurricane using a propensity score matching (PSM) technique. That is, we estimate how the dummy variable for damaged firms is correlated with the number of workers, amount of total assets, and industry dummies using logit and match each damaged firm with another with the closest predicted probability. Second, we estimate the effect of links with firms in neighboring states of the U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich's power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

### Table 7 Results from alternative definition of damaged firms

| Downstream propagation | (1) | (2) |
|------------------------|-----|-----|
| Dummy for any link with damaged suppliers using alternative definition × U.S. dummy | -0.0303*** | -0.0895*** |
| Dummy for any link with damaged suppliers using alternative definition × non-U.S. dummy | 0.0315 | -0.0292 |

| Upstream propagation | (1) | (2) |
|----------------------|-----|-----|
| Dummy for any link with damaged customers using alternative definition × U.S. dummy | -0.0303*** | -0.0895*** |
| Dummy for any link with damaged customers using alternative definition × non-U.S. dummy | 0.0315 | -0.0292 |

| Controls | Yes | Yes |
| Country dummies × Industry dummies | Yes | Yes |
| U.S. state dummies × Industry dummies | Yes | Yes |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes |
| Other disaster dummy | No | No |
| Observations | 11,697 | 11,697 |
| $R^2$ | .186 | .186 |

Notes: Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich's power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level;
**Statistical significance at 5% level;
***Statistical significance at 1% level.
very highly damaged areas, such as Vermont, New Hampshire, Maryland, the District of Colombia, Ohio, Virginia, and West Virginia. In this placebo test, we assume that firms geographically close to damaged firms are similar in attributes to damaged firms.

The results from the first and the second placebo tests are shown in Appendix Tables A6 and A7, respectively. In the tables, some of the effects of the domestic links with firms similar in attributes to or geographically close to damaged firms are positive and significant, while mostly no effect is negative and significant. These results suggest that because firms in the damaged areas around New York City are likely to be more advanced than those in other areas in the world, a firm's links with firms similar to the damaged firms are often positively correlated with the firm's sales growth. An exception is negative and significant coefficients of the dummy for any two-step link with customers near the disaster areas (columns [2] and [4] of Appendix Table A7 in supporting information). However, because we do not find any significant effect of the dummy for any two-step link with firms in the disaster areas (Tables 5 and 6), we do not regard the two sets of evidence as showing the overestimation of the propagation effect through two-step links. Therefore, although our benchmark results may underestimate the propagation effect through direct links, in other words, the true negative effect of

| TABLE 8 | Robustness test using all address information |
|-------------------------------|-----------------|-----------------|
|                               | (1)             | (2)             |
| **Dependent variable: Sales growth 2011–2012** |                 |                 |
| Dummy for any link with damaged suppliers × U.S. dummy | $-0.0211^{**}$ |                 |
|                               | (0.00807)       |                 |
| Dummy for any link with damaged suppliers × non-U.S. dummy | 0.00707 | (0.0154) |
| Dummy for any link with damaged customers × U.S. dummy     |                 | $-0.0491^{***}$ |
|                               | (0.0154)        |                 |
| Dummy for any link with damaged customers × non-U.S. dummy | 0.0205 | (0.0353) |
| Controls                     | Yes             | Yes             |
| Country dummies × Industry dummies | Yes            | Yes             |
| U.S. state dummies × Industry dummies | Yes          | Yes             |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes |
| Other disaster dummy         | No              | No              |
| Observations                 | 11,697          | 11,697          |
| $R^2$                        | .186            | .186            |

Notes: This table presents a variant of the baseline regressions in Tables 5 and 6 where the address for both headquarters and others are used as the location information of firms to identify the firms in disaster-hit areas. Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich’s power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level;
**Statistical significance at 5% level;
***Statistical significance at 1% level.
domestic links directly linked with damaged firms may be larger in absolute terms than our estimates, it is unlikely that our results overestimate the propagation effect.

4.6 | Heterogeneous effects

We further examine the possibility of heterogeneity of effects of damaged partners depending on link characteristics in three ways so as to explore whether there are certain conditions under which the propagation of the negative shocks is alleviated or amplified.

4.6.1 | Specificity of goods

First, we check whether the negative effects are amplified when the damaged suppliers or customers produce specific goods, following Barrot and Sauvagnat (2016). We test with Rauch's (1999) commodity classifications of differentiated goods. Because our data do not include commodity information for each firm, we assume that a firm produces specific goods if its GICS code at the industry level corresponds to any SITC code at the commodity level defined as differentiated goods according to Rauch (1999). The results shown in columns (1) and (2) in panel (A) of Table 9 indicate that the negative effect of links with damaged specific suppliers on their customers in the United States is negative and significant, while that of links with damaged non-specific suppliers is smaller and insignificant. The effect beyond the direct customers when the inputs are specific is negative but insignificant as shown in column (2). As in columns (3) and (4), we obtained similar results when we use alternative definition; a firm is assumed to be a specific goods producer if it has relatively large R&D expenses, that is, their share to its sales is above the 75-percentile value among U.S. firms in the database. Panel (B) of Table 9 presents results for upstream propagation. Unlike the downstream propagation, whether or not the specificity of outputs damaged customers produce matters is not very clear. The coefficients of links with damaged non-specific customers and damaged specific two-step customers are negative and significant. However, those links with damaged specific customers are negative but smaller in absolute terms than those of damaged non-specific customers in columns (1) and (2), whereas they are positive in (3) and (4). The contradictory results between downstream and upstream propagation arise possibly because producers of specific goods do not necessarily utilize specific inputs. Accordingly, when specific-good producers were damaged by the hurricane, their suppliers that did not necessarily produce specific goods may have found alternative customers relatively easily. As a result, the economic shock might not always propagate from producers of specific goods to their suppliers.

Overall, our results in Table 9 point to the important role of input specificity in the propagation of negative shocks, being consistent with Barrot and Sauvagnat (2016). Accordingly, we conclude that the propagation effect is larger when search barriers are higher.

4.6.2 | Network density

Furthermore, we investigate the effect of network structure on the propagation of shocks. In particular, we focus on the density of each firm's egocentric network, as explained in Subsection 2.1. Network density is measured by the local clustering coefficient defined by the ratio of the actual number of links between the focal node's partners/neighbors to the number of all possible pairs among
| (A) Downstream propagation | (1) | (2) | (3) | (4) |
|---------------------------|-----|-----|-----|-----|
| Dummy for any link with damaged specific suppliers × U.S. dummy | $-0.0146^{**}$ | $-0.0157^{**}$ | $-0.106^{***}$ | $-0.105^{***}$ |
| | (0.00664) | (0.00761) | (0.0122) | (0.0148) |
| Dummy for any link with damaged non-specific suppliers × U.S. dummy | $-0.00372$ | $-0.00861$ | $-0.0182^{**}$ | $-0.0111^{**}$ |
| | (0.00721) | (0.00677) | (0.00823) | (0.00556) |
| Dummy for any link with damaged specific suppliers × non-U.S. dummy | 0.0242 | 0.0255 | 0.0657 | 0.0466 |
| | (0.0286) | (0.0328) | (0.0767) | (0.0770) |
| Dummy for any link with damaged non-specific suppliers × non-U.S. dummy | $-0.0201$ | $-0.0257$ | 0.00594 | 0.00742 |
| | (0.0277) | (0.0304) | (0.0160) | (0.0191) |
| Dummy for any 2-step link with damaged specific suppliers × U.S. dummy | $-0.0213$ | 0.0161 | 0.0313^{***} | 0.0103 |
| | (0.0112) | (0.0112) | (0.0168) | (0.0168) |
| Dummy for any 2-step link with damaged non-specific suppliers × non-U.S. dummy | $-0.0186$ | 0.0508^{*} | 0.0508^{*} | 0.0288 |
| | (0.0331) | (0.0112) | (0.0331) | (0.0331) |
| Dummy for any 2-step link with damaged non-specific suppliers × non-U.S. dummy | 0.0479 | $-0.00310$ | 0.0523 | 0.0389 |
| | (0.0441) | (0.0389) | (0.0389) | (0.0389) |
| Controls | Yes | Yes | Yes | Yes |
| Country dummies × Industry dummies | Yes | Yes | Yes | Yes |
| U.S. state dummies × Industry dummies | Yes | Yes | Yes | Yes |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes | Yes | Yes |
TABLE 9 (Continued)

|                              | (1)                      | (2)                      | (3)                      | (4)                      |
|------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
|                              | Differentiated goods     | Differentiated goods     | R&D                      | R&D                      |
| Other disaster dummy         | No                       | No                       | No                       | No                       |
| Observations                 | 11,697                   | 11,697                   | 11,697                   | 11,697                   |
| $R^2$                        | .187                     | .188                     | .186                     | .188                     |

(B) Upstream propagation

- Dummy for any link with damaged specific customers × U.S. dummy: $-0.0386^{***}$ (0.0104)
- Dummy for any link with damaged non-specific customers × U.S. dummy: $-0.0457^{***}$ (0.0147)
- Dummy for any link with damaged specific customers × non-U.S. dummy: $0.0757$ (0.0712)
- Dummy for any link with damaged non-specific customers × non-U.S. dummy: $-0.00293$ (0.0199)
- Dummy for any 2-step link with damaged specific customers × U.S. dummy: $-0.0605^{***}$ (0.0106)
- Dummy for any 2-step link with damaged non-specific customers × U.S. dummy: $0.0180$ (0.0158)
- Dummy for any 2-step link with damaged specific customers × non-U.S. dummy: $-0.0117$ (0.0402)
- Dummy for any 2-step link with damaged non-specific customers × non-U.S. dummy: $-0.0359$ (0.0350)

Controls: Yes
Country dummies × Industry dummies: Yes
TABLE 9  (Continued)

|                      | (1) | (2) | (3) | (4) |
|----------------------|-----|-----|-----|-----|
| **Independent variable:** Sales growth 2011–2012 |     |     |     |     |
| Differentiated goods | Yes | Yes | Yes | Yes |
| R&D                  |     |     |     |     |
| U.S. state dummies × Industry dummies | Yes | Yes | Yes | Yes |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes | Yes | Yes |
| Other disaster dummy | No  | No  | No  | No  |
| Observations         | 11,697 | 11,697 | 11,697 | 11,697 |
| $R^2$                | .187 | .191 | .187 | .190 |

Notes: Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich’s power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level;
**statistical significance at 5% level;
***statistical significance at 1% level.
the partners, representing how densely the focal node’s partners/neighbors are linked with each other (Subsection 3.2). Using network density and its interaction term with the dummies for links with directly damaged firms, we test how network density affects the propagation effect. Because we do not observe clear inverted U-shape relationships between density and propagation of disaster shocks, the results presented do not include the square term of density.

In column (1) of Panels (A) and (B) of Table 10, we find that the interaction term between the dummy variables for links with damaged suppliers or customers for U.S. firms and the local clustering coefficient is negative and highly significant. In contrast, the same columns show that the coefficient of the interaction term for two-step links with damaged U.S. firms is positive. In column (2) of Panels (A) and (B) of Table 10, we disaggregate the shock dummies into the shock from specific goods producers and the one from non-specific goods producers as in the previous subsection, and analyze how differently density affects the degree of propagation depending on the specificity of goods the damaged firms produce, using the interaction term between these disaggregated shock measures and network density. Overall, we find similar results to those in column (1) of Panels (A) and (B); dense networks of firms directly linked to trading partners in disaster areas amplify the negative propagation effect and those of firms indirectly linked to them have a non-negative effect on growth. Although it is not easy to interpret these contrasting findings on direct and two-step links, we pay more attention to the findings on direct links, given the insignificant effect of two-step links in the benchmark regressions (Tables 5 and 6), and weakly interpret them as showing that the negative effects of damaged partners are circulated within dense networks and intensified.

4.6.3 | Multi-layered networks

Last, we check whether the negative effect through supply chains is alleviated or amplified by shareholding links. The literature clearly shows that when firms transact with foreign partners, firms choose either vertical integration with shareholding relationships, that is, intra-firm transactions, or outsourcing without shareholding relationships, that is, arm’s-length transactions (Alfaro et al., 2019; Antrás & Chor, 2013; Del Prete & Rungi, 2017). It is also shown that depending on the organizational mode, changes in production and trade in supply chains in response to an economic shock may vary (Alessandria et al., 2010; Altomonte & Ottaviano, 2009).

When suppliers and customers are in shareholding relationships, parts and components transacted between them are likely to be specific to the firm pairs. Therefore, substituting for parts and components developed from such collaborations between suppliers and customers in exclusive and long-term relationships or selling them to other firms is more difficult than otherwise. Thus, the negative effect of damaged suppliers (customers) on their customers (suppliers) that engage in shareholding relationships with the damaged suppliers (customers) may be larger than on other customers (suppliers) without shareholding relationships. Moreover, the exclusiveness based on the high priority of the transaction based on the strong and long-term relationships may possibly alleviate the propagation of shocks. When suppliers are major shareholders of their customers, or vice versa, damaged suppliers may try to allocate more from the limited amount of their parts and components to the affiliated customers than to unaffiliated customers to maximize profits of the affiliated firm group. Similarly, when customers are major shareholders of their suppliers, or vice versa, damaged customers under limited operations try to buy their inputs more from the affiliated suppliers. Thus, the negative effect of damaged suppliers (customers) on their affiliated customers (suppliers) through shareholding ties may be smaller than on unaffiliated customers (suppliers). The information about shareholding relationships between firms is taken from the Orbis dataset, which is a superset of Osiris. It covers 200 million firms.
**TABLE 10**  Effect of network density

|                                                                 | (1)                        | (2)                        |
|-----------------------------------------------------------------|----------------------------|----------------------------|
|                                                                 | Dependent variable: Sales growth 2011–2012 |                           |
| (A) *Downstream propagation*                                    |                            |                            |
| Dummy for any link with damaged suppliers × U.S. dummy × local clustering coefficient | $-0.265^{***}$ (0.0266)    | $0.102$ (0.0706)           |
| Dummy for any link with damaged specific suppliers × U.S. dummy × local clustering coefficient |                            | $-0.213^{**}$ (0.0287)    |
| Dummy for any link with damaged non-specific suppliers × U.S. dummy × local clustering coefficient |                            |                            |
| Dummy for any 2-step link with damaged suppliers × U.S. dummy × local clustering coefficient | $0.355^{***}$ (0.125)      | $-0.254^{***}$ (0.0289)   |
| Dummy for any 2-step link with damaged specific suppliers × U.S. dummy × local clustering coefficient |                            | $0.529^{***}$ (0.138)     |
| Dummy for any 2-step link with damaged non-specific suppliers × U.S. dummy × local clustering coefficient |                            |                            |
| Dummy for any link with damaged suppliers × U.S. dummy           | $0.00704$ (0.00625)        | $-0.0140$ (0.0108)         |
| Dummy for any link with damaged specific suppliers × U.S.        |                            | $0.00630$ (0.00676)       |
| Dummy for any link with damaged non-specific suppliers × U.S. dummy |                            |                            |
| Dummy for any 2-step link with damaged suppliers × U.S. dummy   | $-0.0462^{***}$ (0.0167)   | $-0.00634$ (0.0166)       |
| Dummy for any 2-step link with damaged specific suppliers × U.S. dummy |                            |                            |

(Continues)
TABLE 10 (Continued)

|                                | (1)                          | (2)                          |
|--------------------------------|------------------------------|------------------------------|
|                                | Dependent variable: Sales growth 2011–2012 |                              |
| Dummy for any 2-step link with damaged non-specific suppliers × U.S. dummy | 0.0192* (0.0112)             |                              |
| Local clustering coefficient   | −0.130 (0.142)               | −0.121 (0.140)               |
| Supply-chain-shock variables for non-U.S. firms | Yes | Yes |
| Controls                      | Yes                          | Yes                          |
| Country dummies × Industry dummies | Yes | Yes |
| U.S. state dummies × Industry dummies | Yes | Yes |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes |
| Other disaster dummy          | No                           | No                           |
| Observations                  | 11,697                       | 11,697                       |
| R²                            | 0.190                        | 0.192                        |

(B) Upstream propagation

|                                |                              |                              |
|                                | 1941*** (0.0403)             | 2.667*** (0.0573)            |
| Dummy for any link with damaged customers × U.S. dummy × local clustering coefficient |                              |                              |
| Dummy for any link with damaged specific customers × U.S. dummy × local clustering coefficient | −2.667*** (0.0573)            |                              |
| Dummy for any link with damaged non-specific customers × U.S. dummy × local clustering coefficient | −0.416*** (0.0524)            |                              |
| Dummy for any 2-step link with damaged customers × U.S. dummy × local clustering coefficient | 0.00153 (0.0522)             | −0.0467 (0.0312)             |
| Dummy for any 2-step link with damaged specific customers × U.S. dummy × local clustering coefficient |                              |                              |
TABLE 10  (Continued)

| (1) | (2) |
|---------------------------------------------|------|
| **Dependent variable: Sales growth 2011–2012** |      |
| Dummy for any 2-step link with damaged non-specific customers \(\times\) U.S. dummy \(\times\) local clustering coefficient | 0.0814*  
  \( (0.0453) \) |
| Dummy for any link with damaged customers \(\times\) U.S. dummy | 0.103***  
  \( (0.00884) \) |
| Dummy for any link with damaged specific customers \(\times\) U.S. dummy | 0.204***  
  \( (0.00782) \) |
| Dummy for any link with damaged non-specific customers \(\times\) U.S. dummy | \(-0.0332***\)  
  \( (0.00728) \) |
| Dummy for any 2-step link with damaged customers \(\times\) U.S. dummy | \(-0.0146\)  
  \( (0.0199) \) |
| Dummy for any 2-step link with damaged specific customers \(\times\) U.S. dummy | \(-0.0456***\)  
  \( (0.0102) \) |
| Dummy for any 2-step link with damaged non-specific customers \(\times\) U.S. dummy | 0.00134  
  \( (0.0159) \) |
| Local clustering coefficient | 0.00430  
  \( (0.0577) \)  
  \(-0.0118\)  
  \( (0.0649) \) |
| Supply-chain-shock variables for non-U.S. firms | Yes | Yes |
| Controls | Yes | Yes |
| Country dummies \(\times\) Industry dummies | Yes | Yes |
| U.S. state dummies \(\times\) Industry dummies | Yes | YES |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes | Yes |
| Other disaster dummy | No | No |
### TABLE 10  (Continued)

| Observations | (1)     | (2)     |
|--------------|---------|---------|
| R²           | 11,697  | 11,697  |

**Dependent variable: Sales growth 2011–2012**

*Notes: Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers (all in logs), Bonacich's power centrality, isolates dummy, and one link dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.*

*Statistical significance at 10% level;**statistical significance at 5% level;***statistical significance at 1% level.
around the world including non-listed small and medium enterprises. We merge it with supply chain data as we did for Osiris. Using the merged data, we test whether propagation from disaster-hit firms to their suppliers and customers through supply chains is different if firms are also linked through a shareholding relationship, forming a multi-layered network.

The result reported in column (1) of Table 11 indicates that shareholding links are more likely to amplify negative effects of damaged suppliers as suggested by the bigger negative coefficient, confirming our presumption above. For upstream propagation, column (2) of Table 11 shows that the effect of damaged customers with shareholding relationship is positive whereas that of damaged customers without shareholding relationship is negative. Although it is not so clear why the former is positive significant, these results suggest that the shareholding relationship may alleviate upstream propagation. This is probably because damaged customers under limited operations due to the direct

|                            | (1)                          | (2)                          |
|-----------------------------|------------------------------|------------------------------|
| Dummy for any link with damaged suppliers in shareholding relationships × U.S. dummy | −0.0736*** (0.00998)         | 0.0910*** (0.0312)           |
| Dummy for any link with damaged suppliers not in shareholding relationship × U.S. dummy | −0.0172** (0.00819)         | −0.0586*** (0.0153)          |
| Dummy for any link with damaged suppliers × non-U.S. dummy | 0.00937 (0.0151)            | 0.0213 (0.0357)              |
| Controls                    | Yes                          | Yes                          |
| Country dummies × Industry dummies | Yes                          | Yes                          |
| U.S. state dummies × Industry dummies | Yes                          | Yes                          |
| Dummies for the end month of the accounting period and their interaction with supply-chain-shock variables | Yes                          | Yes                          |
| Other disaster dummy        | No                           | No                           |
| Observations                | 11,697                       | 11,697                       |
| $R^2$                       | .186                         | .186                         |

Notes: Robust standard errors clustered at the country level are in parentheses. Controls include sales growth from 2010 to 2011, the amount of total asset in log, the number of employees in log, firm age, and sales per worker in log, the number of suppliers, customers, domestic suppliers, domestic customers, 2-step suppliers, 2-step customers, other suppliers of customers, U.S. suppliers, U.S. customers, U.S. 2-step suppliers, U.S. 2-step customers, other U.S. suppliers of customers, capital shareholdings links, capital shareholdings links × non-US dummy (all in logs), Bonacich’s power centrality, and isolates dummy. Single terms of each interaction term are also included. When we use triple interactions, we also use single terms and double interactions when necessary.

*Statistical significance at 10% level;
**statistical significance at 5% level;
***statistical significance at 1% level.
disaster damages put priority on their affiliated firms when they buy inputs from suppliers so that they can maximize their affiliated group profits. Since disaster damaged firms are often forced limited operations instead of complete halts, the priority of transaction can differentiate the level of disaster shock propagations.

5 | CONCLUSIONS

In this study, we take Hurricane Sandy, which struck the east coast of the United States in 2012, as a source of negative economic shocks and examine whether the shock propagated to firms outside the disaster area through global supply chains. Specifically, using firm-level data on global supply chains, we analyze how sales growth of firms is affected by their direct and indirect suppliers and customers directly damaged by the hurricane.

Our results show that direct links with suppliers and customers suffered from a hurricane decreased the sales growth of firms within the United States, while the effect on firms outside the United States was not significant. Therefore, we conclude that negative economic shocks by a hurricane propagate through domestic supply chains, which is consistent with the evidence from the Great East Japan Earthquake (Carvalho et al., 2016). Although both hurricanes and earthquakes are “low-probability-high-consequence events” (Skidmore & Toya, 2002), geologic disasters such as earthquakes are found to be associated with worse macroeconomic recovery than climatic disasters. This study, finding significant propagation of hurricane shocks, suggests that even climatic disasters can give substantial damage to supply chains. Our further analysis shows a larger propagation effect on U.S. firms when inputs are specific, consistent with a previous study. These results suggest that search barriers amplify the propagation of shocks through supply chains and thus, source multiplication or preparation for the emergency substitution is needed to suppress the damage from supply chain disruption. In addition, we find that the propagation effect on U.S. firms is larger when their ego network is denser, that is, their partners are connected with each other. All these findings imply that supply-chain links with diverse partners on networks lead to economic resilience to the propagation of negative shocks.

Although our study is unique in that we use a hurricane shock, measures of network characteristics, and global supply chain data to investigate the propagation of disaster shocks through supply chains, there are several limitations. First, our data are limited to publicly listed firms and their major supply-chain relationships because the internationally comparable financial data is mostly limited to publicly listed firms and our major data source of supply chain information relies on public information such as financial reports and websites. Although we confirmed that the coverage of the publicly listed firms and their major links in our data is as high as that in the Compustat Segment files used in the previous study, ignoring smaller firms and links among them may have underestimated the propagation of shocks. Second, because our data are not at the establishment level but at the firm-level, we identify firms directly damaged by the hurricane by the location of their headquarters. If a major plant of a firm whose headquarters is not located in the disaster area is in the disaster area, we classify this firm as one not directly damaged by the hurricane. This may also have resulted in the underestimation of the true effect of the hurricane, although the existing studies, such as Barrot and Sauvagnat (2016) and Carvalho et al. (2016), embody the same data limitation. However, it should be emphasized that regardless of the two caveats we find a significant negative propagation of shocks by a hurricane within a country. One of the characteristics of this study is that we find the negative propagation from relatively large firms in urban areas, which may be useful to discuss the supply chain risk by disasters in urban areas. Past studies focusing on a single disaster case, find such a negative propagation of disaster shocks from rural firms because of the
characteristics of the disaster-hit region. Although we provide another evidence of the propagation of disaster shocks under different conditions, more studies are needed to verify the external validity of disaster impacts on supply chains because different disasters may bring different consequences. In addition, our data lack sufficient information on quarterly-level sales, products' prices, and quantities. Because of this limitation, we cannot conduct a detailed analysis on how the impact changes over time nor how price changes affect the results. For the latter, by utilizing industry information as well as location information, we consider price changes at the level of industry-country pairs for non-US firms and industry-state pairs for U.S. firms, but we could not consider price changes at the firm level. Finally, although our results imply benefits of network diversification and flexibility in terms of economic resilience, we did not conduct any cost-benefit analysis. Thus, the investigation of the optimal level of diversification is left for future study.

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DATA AVAILABILITY STATEMENT
The data used in this study are unsuitable to post because our licensing contract with the data vendor, FactSet Revere, does not allow us to do so, although other researchers can obtain access to the exact data by obtaining a license.

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ENDNOTES
1 The corresponding average found by Barrot and Sauvagnat (2016), 1.38, who use the Compustat Segment files to identify suppliers and customers.

2 The mean for US firms reported in Barrot and Sauvagnat (2016) is 0.711.

3 Some of the coefficients of the interaction terms are negative, suggesting that the propagation effect is larger for firms with particular fiscal year-end months than those whose fiscal year-end month is December, while others are positive, suggesting the opposite.

4 Although the benchmark results focus on sales growth from 2011 to 2012, we repeat the estimation using sales growth from 2011 to 2013 as a dependent variable. The results are in Appendix Table A8 in supporting information.

5 GICS codes are more aggregated than SITC. We classify firms as specific if its GICS code covers at least one SITC code that Rauch (1999) classifies as “differentiated goods.”.
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