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Production network, propagation of firm-level shocks, supply-chain diversity

JEL Classification

L14, E23, E32

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The Effect of Supply Base Diversification on the Propagation of Shocks*

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Abstract

This paper studies the role of supply base diversification on the propagation of shocks through production networks. We identify exogenous shocks with the occurrence of natural disasters in the US between 1978 and 2017. We find that affected suppliers reduce customers' sales growth by $\approx 25\%$, on average. Notably, firms that source intermediate inputs across many suppliers, geographies, or industries attenuate shocks to their suppliers by $\approx$ 60-70%. We interpret our empirical findings using a general equilibrium model of production networks. First, we establish that diverse firms exhibit gross substitutability among inputs relative to non-diverse firms, suggesting diverse firms insulate themselves by substituting away from disrupted suppliers. By estimating the structural elasticity parameters, we find real GDP would have been $\approx$ \$740 billion lower in 2017 in the absence of diversified firms.

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1 Introduction

The Covid-19 pandemic plunged global supply networks into disarray, with 94% of Fortune 1000 companies experiencing supply chain disruptions (Fortune, 2020). To firms, it has served as a stark reminder of the importance of supply base diversification. While a shock might not directly impact a firm, an event negatively affecting its suppliers may propagate along the supply chain, adversely affecting its performance. Anecdotal evidence suggests that firms source inputs from a small number of suppliers, exposing themselves to supply risks.[1] For example, after a major fire destroyed the production facility of Toyota's major supplier in February 1997, Toyota was left without a crucial component for its braking system and was forced to halt production (Nishiguchi and Beaudet, 1998). In the same year, Boeing lost USD 2.6 billion when two key suppliers failed to deliver parts on time (The New York Times, 1997). More recently, Nike factories in Vietnam were forced to close due to Covid-19 lockdowns, resulting in the loss of 100 million shoes (The Wall Street Journal, 2021). While these examples highlight the potential for significant output losses associated with a lack of supplier diversity, there exists no systematic study that quantifies the effect of supply base diversification on the propagation of shocks.[2]

We begin by conducting two intermediate empirical exercises to study how supply base diversification affects firm performance. First, in a similar manner to Atalay et al. (2011) and Barrot and Sauvagnat (2016), we use Compustat's *Customer Segments* dataset to create a network of supplier-customer links between publicly traded US firms from 1978–2017. Our panel data contains $\approx$ 90,000 firm-quarter observations, allowing us to observe the impact of supplier shocks on the sales growth of customer firms. Second, to study how shocks transmit through the supply chain, we identify exogenous firm-level disruptions with the occurrence of 52 major natural disasters in the US between 1978–2017, as in Barrot and Sauvagnat (2016). As a

[1] Choi and Krause (2006) discusses the risks of a single-sourcing strategy, where a focal firm is exposed to greater risk due to over-reliance on its suppliers.

[2] Supply shortages associated with Covid-19 disruptions have motivated public debate on increasing supply chain resilience. For example, the French Minister Of Economy and Finance argues that "years of offshoring in the pharmaceutical sector has led us to a situation where 80% of active pharmaceutical ingredients are today produced outside of the Union, an over-reliance which created severe supply breakdowns of medicine used in reanimation during the crisis ... We should develop strategic stockpiling, geographic diversification of supply and, where appropriate, increase European production capacity, to build up our autonomy in these strategic areas" (Le Maire, 2020).

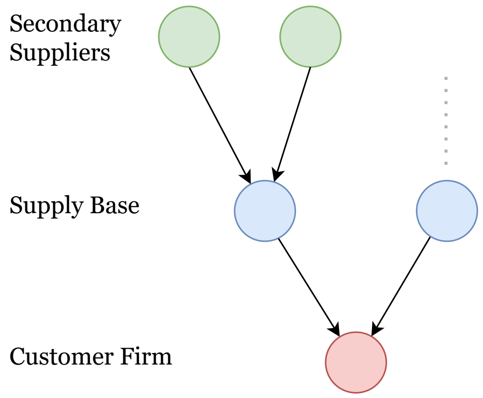

Figure 1: Illustration of a Supply Chain

Note: This figure illustrates the supply chain of a customer firm (red node). The customer firm's supply base comprises two immediate suppliers (blue nodes). Green nodes represent secondary suppliers.

baseline, we find similar supplier-to-customer propagation effects as Barrot and Sauvagnat. A firm's sales growth decreases by approximately three percentage points if one of its suppliers is hit with a natural disaster four quarters back.

Once we (re)establish the propagation of supply shocks, we quantify the extent to which firms with a diversified supply base are insulated from shocks to their suppliers relative to non-diversified firms. As Figure 1 shows, the supply base is the portion of a firm's supply chain that it transacts with directly.[3] In this paper, a 'diverse firm' is a firm whose intermediate input purchases span many i) suppliers, ii) geographies, or iii) industries. Specifically, we calculate a Herfindahl index to measure how a customer firm's total purchases in a given quarter are spread over the three dimensions mentioned above. For each index, a firm with a value closer to zero is regarded as more diverse, while a firm with an index closer to one has most of its purchases concentrated on a single supplier. Our measures of customers' diversity reflect that both regional and sectoral components are essential in understanding the aggregate implications of local shocks (Caliendo et al., 2017. Irrespective of the definition of diversity, diverse firms experience 60-70% smaller decreases in sales growth in response to supply shocks relative to non-diverse firms. Our findings thus support the hypothesis that supply base diversity attenuates the propagation of supply shocks.

[3]Firms in the supply base are also referred to as the customer firm's 'primary suppliers' or 'first-tier suppliers.'

A potential threat to identification is the possibility that firms may endogenously choose to have a (non-)diversified supply base. Diversity may be an emergent property of firms already more adept at managing supply base risks. In this case, it would not be supply base diversity that ultimately causes the attenuation of shocks but rather some other underlying firm characteristic. For example, firms with better supply chain management systems may take on more suppliers while also being better equipped to manage supplier shocks. Take the case of Walmart, the firm with the most reported suppliers in the sample period.[4] Walmart has an 'Emergency Operations Centre,' which operates 24/7 and is responsible for re-routing supplies when supply disruptions occur (Webb, 2020). If diversity is positively (negatively) correlated with (un)observable firm characteristics that may affect the firm's sales growth, this may over (under) estimate the benefits of diversity.

First, we address this issue by controlling for fixed effects at the firm, year-quarter, and fiscal quarter levels. In addition, we also control for firm size, productivity, and the number of suppliers in our regressions, amongst other controls. After partialling out the influence of a vector of controls discussed above, we use plausibly idiosyncratic variations in our diversity measures. Next, as a direct test, we show that our diversity measures are uncorrelated with various firm characteristics that may affect firm sales growth. Third, we check if the destruction of old customer-supplier links or the creation of new connections is correlated with the suppliers' geographic location, which may be more or less susceptible to natural disasters. For example, Figure 6 shows that the eastern seaboard is very vulnerable to natural disasters. We check if the destruction of old links is more likely when a supplier is from a disaster-prone area. Finally, we also test whether new links formed are more likely to include firms that are not in disaster-prone areas. We do not find evidence of systematic selection away from suppliers in disaster-prone areas.

Our reduced-form estimates provide evidence that diverse firms' sales are not significantly affected when a supplier is hit with a shock. However, our empirical analysis of Section 3 does not quantify the impact of supply base diversity on aggregate output, which is the more welfare-relevant variable and is of greater interest to macroeconomic policymakers. To this end, we build a general equilibrium model of production networks à la Long and Plosser (1983), and Baqaee and Farhi (2019) to estimate the benefit of supply base

[4] In 2002, Walmart was reported as a customer by 142 firms in the dataset.

diversity in terms of real GDP. In the model, firms use a constant-elasticity-of-substitution (CES) production technology that transforms capital and intermediate inputs into output. Notably, diverse firms differ from non-diverse firms in their ability to substitute between inputs and, therefore, behave differently from one another when producers are subject to supply shocks. To align with our empirical analysis, we model natural disasters as capital-augmenting idiosyncratic shocks to firms, which reduce firms' ability to use capital to produce. The idea is that disasters partially destroy the economy's capital stock, which limits firms' production possibilities.

Our main theoretical result shows that firms' substitution behavior affects real GDP to the second-order of approximation (similar to Baqaee and Farhi, 2019). We derive an expression that computes the change in aggregate output attributed to the behavior of the economy's diverse firms. We refer to this as the macroeconomic benefit of supply base diversification. The expression is increasing in the elasticity of substitution of diverse firms, which is the only free parameter required to estimate how supply base diversity impacts real GDP. Thus, in a preliminary exercise, we use our model to estimate firms' elasticities of substitution using variation in sales and sector-level production network data. We find evidence that production functions are Cobb-Douglas for non-diverse firms (i.e., these firms have a unitary elasticity of substitution). In contrast, inputs are gross substitutes for diverse firms (with an elasticity of substitution ≈ 2). With these estimates in hand, we use our formula to calculate the counterfactual level of real GDP without the substitution behavior of diverse firms, which is achieved by setting these firms' elasticity of substitution to one. Our counterfactual exercise implies that real GDP would have been $\approx$ \$740 billion lower in 2017 in the absence of supply base diversity, indicating that diversity provides substantial macroeconomic benefits.

Related literature. Our paper is most closely related to the recent empirical literature that uses natural disasters to establish the propagation and amplification of microeconomic shocks through input-output linkages. Barrot and Sauvagnat (2016) show that the transmission of shocks from supplier to customer increases with the input specificity of suppliers' inputs (as measured by suppliers' R&D expenditure, number of patents, and degree of tradability on international markets). In contrast, we leverage US natural disasters to study how propagation varies depending on customer firms' attributes, as opposed to supplier characteristics. We find the transmission of shocks from suppliers to customers is attenuated for more diverse customer firms. This finding is not in contradiction with Barrot and Sauvagnat (2016); as we show in Section 3.5, input specificity and customer diversity are both important drivers of the transmission of supply shocks within the production network. Relatedly, Boehm, Flaaen and Pandalai-Nayar (2019a) study the cross-country transmission of the 2011 earthquake in Japan by documenting that US affiliates of Japanese multinationals experienced substantial reductions in output following the disaster. In a similar study, Carvalho et al. (2021) document extensive output losses of Japanese firms whose direct and indirect trading partners were struck by the Great Japanese Earthquake in 2011. While the empirical literature has focused on input-output linkages as a source of amplification of disruptions, we show how diversified customers are insulated against shocks to their suppliers, mitigating the extent of propagation through the network.

This paper also relates to the theoretical literature that studies the role of input-output linkages as a mechanism through which microeconomic shocks propagate and amplify into sizeable aggregate fluctuations. Building on Long and Plosser (1983), studies such as Acemoglu et al. (2012); Acemoglu, Ozdaglar and Tahbaz-Salehi (2017) and Baqaee and Farhi (2019) characterize conditions under which microeconomic disturbances propagate through the production network to generate fluctuations in aggregate economic variables.[5] We contribute to this literature by quantifying how diverse firms mitigate the aggregate effects of negative supply shocks. In our model, diverse and non-diverse firms differ in their ability to substitute between inputs, which affects how aggregate output responds to the shocks. In this sense, we also contribute to the literature that studies the implications of non-unitary elasticities of substitution for the propagation and aggregation

[5]Early contributions to this topic include Hulten (1978), Jovanovic (1987), Durlauf (1993), and Horvath (1998, 2000). Gabaix (2011), Carvalho and Gabaix (2013), and Amiti and Weinstein (2018) discuss the role of firm size distribution in amplifying micro shocks into aggregate fluctuations. A related literature studies the role of linkages in propagating shocks in the presence of distortions (see, for example, Bartelme and Gorodnichenko, 2015; Caliendo, Parro and Tsyvinski, forthcoming; Grassi, 2017; Altinoglu, 2021; Baqaee, 2018; Boehm, 2020; Boehm and Oberfield, 2020; among others). Jones (2011, 2013) and Bigio and La'O (2020) study properties of inefficient (Cobb-Douglas) production networks with generic "wedges" while Baqaee and Farhi (2020) study nonparametric and CES networks. Studies like Elliott, Golub and Leduc (2022) and Carvalho, Elliott and Spray (2022) study how complex supply chains and bottlenecks can contribute to macroeconomic fragility. See Carvalho (2014) and Carvalho and Tahbaz-Salehi (2019) for a thorough review of the literature on production networks.

of shocks in production networks (see, for example, Horvath, 2000, Atalay, 2017, and Baqaee and Farhi, 2019).[6]

While the macroeconomic literature has typically focused on input-output linkages as a source of amplification of shocks, a separate literature in international trade has studied how global supply chains (GSCs) could play a role in shock mitigation.[7] For example, Caselli et al. (2020) shows that integration in GSCs tends to decrease vulnerability to sectoral shocks. Using a quantitative model, they argue that cross-border diversification has reduced economic volatility for most countries since the 1970s. Relatedly, D'Aguanno et al. (2021) use a multi-country macroeconomic model to show that a reduction in GSC integration would impose economic costs without reducing aggregate volatility. Similarly, Antràs (2021) notes that economies of scale make firms reluctant to dismantle GSCs in the face of temporary shocks since firms incur high sunk costs when choosing global sourcing strategies. Antràs (2021) goes on to argue that the "sticky" nature of GSCs contributed to the V-shaped recovery in world trade following the global financial crisis. In line with this literature, we find that diversified supply chains can insulate firms against shocks, lowering the risks associated with supply disruptions. Furthermore, we find supply base diversification has a positive and non-trivial impact on aggregate output, reducing the aggregate effect of crises.

The rest of the paper is structured as follows. Section 2 details the data used and provides summary statistics. Section 3 presents the empirical model and results (including a battery of robustness tests). Section 4 provides a theoretical model to quantify the macroeconomic benefit of supply base diversity. Section 5 concludes. Proofs and supplementary results appear in the Appendix.

[6] Papers such as Boehm, Flaaen and Pandalai-Nayar (2019b), Peter and Ruane (2020), Carvalho et al. (2021) and Oberfield and Raval (2021) obtain estimates of elasticities of substitution at different levels of aggregation and time horizons. Using our model, we estimate elasticities for diverse and non-diverse firms, finding inputs to be gross substitutes for diverse firms and gross complements for non-diverse firms.

[7] See Baldwin and Freeman (2022) for a detailed overview of the GSC literature.

2 Data and Summary Statistics

2.1 Firm Financial Data

We use firm-level financial data from Compustat's *North America Fundamentals Quarterly* database. This dataset contains quarterly information on firm sales (in dollars), cost of goods sold, and SIC and NAICS industry classification codes, among other information for all publicly listed firms in the US. We restrict the sample to firms headquartered in the US between 1978-2017.[8] We deflate sales and cost of goods sold (COGS) using the GDP price index from the Bureau of Economic Analysis so that growth in these variables reflects firms' performance, not price dynamics.[9]

To reduce measurement error and increase the precision of the estimates obtained, we restrict the sample to firms that report in calendar quarters, ensuring consistency when matching firm performance with natural disasters, which are also reported at the calendar quarter-county level.[10] This avoids a situation whereby a firm reports data for its first quarter at the end of February and is then hit by a natural disaster in March. In this scenario, the firm's financial data for the first quarter of the year would be largely unaffected, but the firm would be treated as having been hit by a natural disaster in the regressions.

A 4-digit SIC code represents a firm's industry. Since the current industry classification of a firm may be different from its historical classification, we use Compustat's historical SIC codes to adjust any changes to firms' SICs over time. To control for industry fixed effects, we generate indicator variables for the 48 Fama-French industries using the adjusted 4-digit SIC codes, as per Fama and French (1997).

2.2 Firm Location

Compustat also provides information on every firm's most recent location (ZIP code) (or its headquarters, in case a firm has multiple plants). Since a firm's location may change over time, we achieve greater veracity by up-

[8]Customer-supplier transactions data is only available from 1978 onwards.

[9]We winsorize all continuous variables at the 1st and 99th percentiles.

[10]This does not necessarily mean that the fiscal quarter of a firm should be equal to the calendar quarter, only that we limit the sample to firms that report at the end of March, June, September, and December (irrespective of when their fiscal year ends). Our results do not change if we include firms reporting outside calendar quarters.

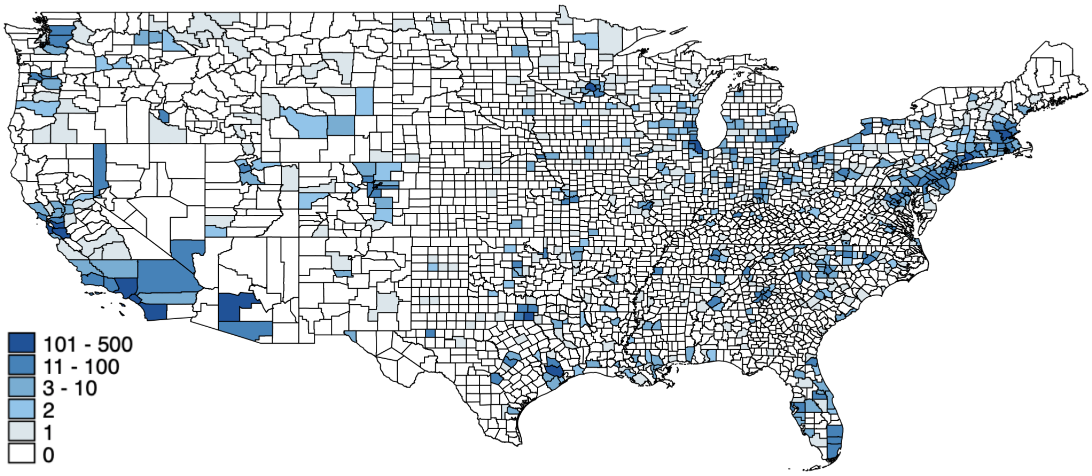

Figure 2: Distribution of Firm Headquarters by U.S. County (1978-2017)

Note: This figure depicts the distribution of firm headquarters across our sample of U.S. firms between 1978-2017 at the county level. Shading represents the number of distinct firms reporting the given county as its headquarters location in at least one quarter. Location data are drawn from Compustat and adjusted to reflect historical changes in the location of headquarters.

dating historical ZIP codes for all quarters from 2007 to 2017 using CRSP's *Quarterly Update Company History* dataset, which contains changes in firm location during this time period. For observations before 2007, the ZIP code accurate as of the first quarter of 2007 is used. Any residual measurement error for firm location may lead to firms being incorrectly assigned as being in a county (un)affected by a natural disaster, which would bias estimates against finding a direct effect of natural disasters on firms.

We match the adjusted ZIP codes to the *US ZIP Codes* database, which contains the latitude and longitude for all 41,696 private and USPS ZIPs.[11] We measure the distance between two firms, in kilometers, as the geodesic between these coordinates according to Vincenty's formula (Vincenty, 1975). While ZIP codes provide a more precise estimate of the distance between firms, the disaster data are reported at the county level. To assign a firm's location to a county, we match ZIP codes to their corresponding county using US *ZIP Code* database. If a firm's ZIP code overlaps multiple counties, we manually assign the county identifier (FIPS) using the firm's street address. Figure 2 illustrates the dispersion of firm headquarters, over the entire sample period, on a county-level US map. As the figure shows, firms tend to cluster around business and industrial hubs, as one might expect.

[11]The coordinates are measured at the centroid of the ZIP code's land area.

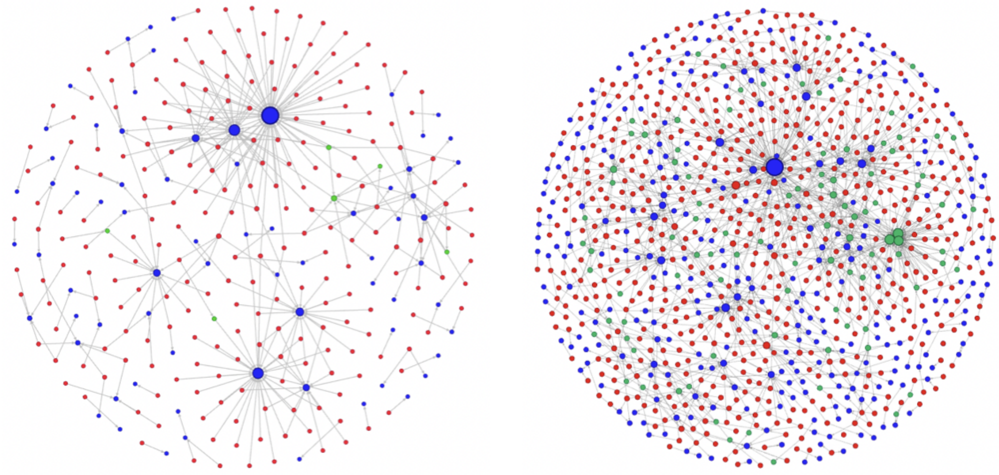

Figure 3: Comparison of US Supply Network (1978 - 2017)

Note: This graph illustrates the network of US firms as reported in Compustat's *Customer Segments* dataset in 1978 and 2017. Each node represents a firm; red nodes are suppliers, blue nodes are customers, and green nodes represent firms that are both suppliers and customers. The size of each node is proportional to the in-degree (of customers) or out-degree (of suppliers) of that node (i.e., the number of edges it has). The edges connecting the nodes represent an active relationship between the firms in that year. In 1978, there were 1,935 nodes connected by 1,979 edges, and in 2017 there were 2,657 nodes connected by 3,019 edges. The graph is created using the Fruchterman Reingold algorithm in Gephi.

2.3 Supplier-Customer Links

The analysis relies on identifying active supplier-customer relationships to identify the propagation of shocks along supply chains. To identify firms' customers, we exploit Financial Accounting Standard No. 131, which requires public firms to report any customer accounting for 10 percent or more of total annual sales.

> **Financial Accounting Standard No. 131: Information about Major Customers**
> *An enterprise shall provide information about the extent of its reliance on its major customers. If revenues from transactions with a single external customer amount to 10 percent or more of an enterprise's revenues, the enterprise shall disclose that fact, the total amount of revenues from each such customer, and the identity of the segment or segments reporting the revenues.*
> Financial Accounting Standards Board (1997)

Compustat's *Customer Segments* dataset contains information on the iden-

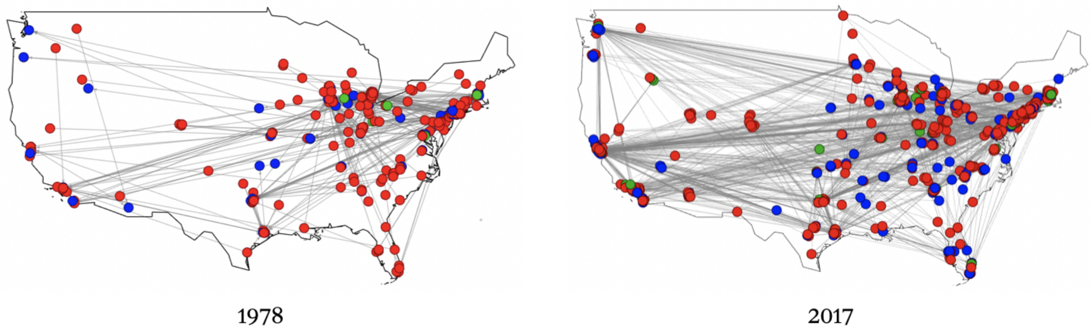

Figure 4: Geographic Distribution of US Supply Network (1978 - 2017)

Note: This graph illustrates the network of US firms as reported in Compustat's *Customer Segments* dataset in 1978 and 2017. Each node represents a firm; red nodes are suppliers, blue nodes are customers, and green nodes represent firms that are both suppliers and customers. The edges connecting the nodes represent an active relationship between the firms in that year. The nodes are plotted on a map of the US, showing the location of the firm's headquarters as reported in Compustat. In 1978, there were 1,935 nodes connected by 1,979 edges, and in 2017 there were 2,657 nodes connected by 3,019 edges.

tity of suppliers and their reported customers, the date these relationships are reported, and the revenue that these relationships represent for the supplier.[12] The customer names entered by suppliers are often inconsistent with the official company name recorded by Compustat (e.g. "Coca-Cola Co" v.s. "Coca Cola Inc"). We use a systematic process of manual adjustments to these text strings to create a comprehensive dataset of active supplier-customer relationships, which we merge with the corresponding firms' financial data. This results in $\approx$ 26K unique customer-supplier pairs across $\approx$ 360K customer-supplier-quarter observations. The average supplier-customer relationship in the sample lasts 15 quarters.

Figure 3 illustrates the supplier-customer production network for the first year (1978) and last year (2017) of the sample. As the figure shows, there is a significant increase in the number of firms (nodes) and connections per firm (edges per node) over time, signifying a substantially denser network in 2017.[13] Figure 4 shows the change in the geographical dispersion of the firm-level production network between 1978 and 2017. As the graphs show, a significant proportion of customer-supplier links are inter-state, providing

[12]This supplier-customer relationship data has been used in Fee, Hadlock and Thomas (2006), Atalay et al. (2011), Barrot and Sauvagnat (2016) and Chu, Tian and Wang (2019), among other studies.

[13]Alternatively, a denser production network may reflect improved reporting standards or data collection. Given the mandatory nature of SFAS 131 and the consistency of Compustat's reporting, we suppose this is not the case, as reporting errors are likely stochastic and, thus, time-invariant.

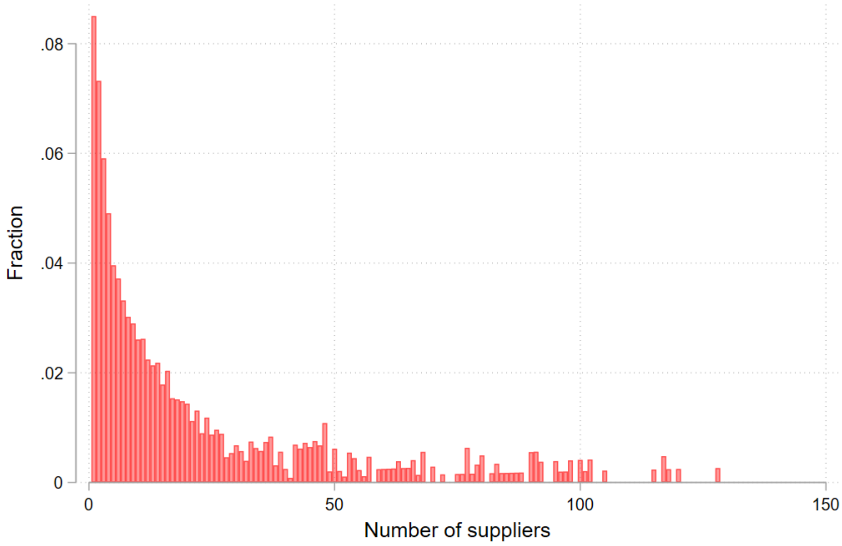

Figure 5: Distribution of Firms' Number of Suppliers

Note: This figure shows the distribution of firms' number of suppliers, with data including all years between 1978 to 2017. Observations are at the firm-year level for all firms recorded as having at least one supplier. The data is sourced from Compustat's *Customer Segments* dataset.

an ideal setting to examine the transmission of supply shocks (due to natural disasters) from affected suppliers to customers of different geographies. We also exploit the heterogeneity of firms' locations to study how geographical (supply base) diversity attenuates supply shocks.

Since supplier-customer relationships are reported annually and our firm financial data is quarterly, we assume (following Barrot and Sauvagnat, 2016) that supplier-customer relationships are active for all quarters between q_0+1 and q_L+4. Here q_0 (q_L) is the quarter that the relationship is first (last) reported.[14] This is a conservative approach, as the relationship may not be active in some of the intermediate years, which would bias against finding a propagation effect. Finally, we exclude all relationships where the supplier and customer are located within a 300-kilometer radius. This reduces the direct effect the disaster may have had on the customer's sales, isolating the propagation of shocks from the direct demand-side effect the disaster may have had on the customer. Figure 5 plots the distribution of customer firms in-degree (number of suppliers) for the resulting sample. It is posit-

[14]The rationale for this is that q_0+1 is the first quarter we can be certain that the relationship was active, after which it remains active until an unknown time between q_L and q_L+4.

ively skewed, with a median supplier count of 12 and a mean of 23.6.

The customer and supplier samples together represent approximately 75% of the total sales across all Compustat firms in the US economy in the time period sampled. To this extent, it appears to be a representative sample of publicly traded firms in the US economy, comprising a significant proportion of aggregate economic activity. A key limitation of the Compustat data is that customer-supplier relationships representing less than 10% of the supplier's sales are not reported. Consequently, the supply network created accounts for only a small proportion of the suppliers in the US. The accounting standard creates a bias for smaller suppliers reporting larger customers that make up a relatively large proportion of their sales. Barrot and Sauvagnat (2016) conduct robustness tests using an alternative dataset of private firms and find that the propagation of supply disruptions occurs in similar proportions across publicly and privately listed firms. Furthermore, using the same data, Atalay et al. (2011) finds the fraction of suppliers omitted due to the 10% threshold to be statistically similar across customers with many or few suppliers. This result is particularly important in the context of our study as a customer's in-degree, one of the diversity measures, is not biased (in a relative sense) due to the 10% threshold. This is because all our diversity measures are based on a firm's position *relative* to other customer firms at any given quarter.

2.4 Natural Disasters

Natural disaster data are compiled from two sources. EM-DAT's public database includes all disaster events across our sample period. It provides information on the disaster start and end date, type, event name, the geographic region affected (typically at the state level), and total estimated damage.[15] EM-DAT records a disaster as an event that meets one or more of the following three criteria: (i) 10 or more deaths, (ii) 100 or more people affected, or (iii) declaration of a state of emergency. A shortcoming of this dataset is that it does not provide information at the county level. This can be an issue since disasters often affect only certain counties within a given state.

To address this issue, we use FEMA's *OpenFEMA Disaster Declarations* dataset. The FEMA dataset provides all major U.S. Disaster Declarations

[15] 'Damage' is an estimate of both direct and indirect damage. We cross-check damage estimates with publicly reported data for all disaster events and adjust damages for inflation.

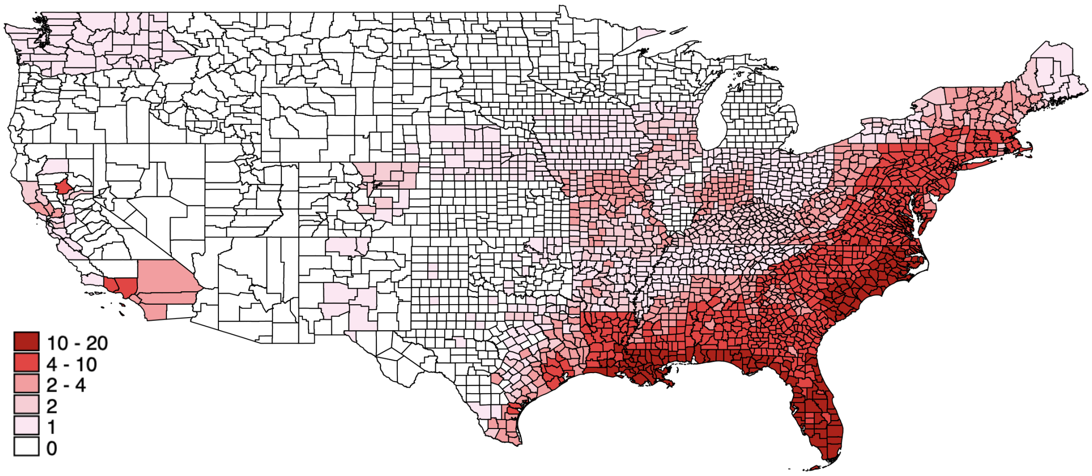

Figure 6: Frequency of Natural Disasters by U.S. County (1978-2017)

Note: This map shows the frequency of major natural disaster events by U.S. county, spanning from January 1978 to December 2017. Major disasters are defined as causing over USD 1 billion in under 30 days. It draws on an aggregation of data from EM-DAT and FEMA.

and Emergency Declarations across the sample period, as well as the disasters' start and end date, type, county, state, event name, and a unique ID. We manually assign these unique IDs to the disaster declarations from the EM-DAT dataset to identify counties affected by the disaster. In the first instance, we match based on corresponding event names. Where disasters do not have a name, they are matched based on the start and end dates, disaster type, and states affected. In case there is ambiguity, we take a conservative approach and omit the disaster from the study. The resulting dataset contains county-level data for all US natural disasters between 1978 and 2017, in addition to damage estimates and the duration of each disaster. Figure 6 shows the frequency of major natural disasters by US county between January 1978 and December 2017.

In line with Barrot and Sauvagnat (2016), we include all disasters with damages exceeding $1 billion (inflation-adjusted to 2017 dollars) that lasted less than 30 days. This restricts the analysis to disasters that had a major impact, causing significant damage over a short period and consequentially disrupting firms' output. Between 1978 to 2017, there were 52 major natural disasters. As Figure 7 shows, most of these disasters are hurricanes, the most destructive being Hurricane Katrina, with damages over $150 billion. The average damage caused is USD 16.1 billion. The disasters' localized and random nature makes them a plausibly exogenous firm-level supply shock. As we show in Section 3, shocks propagate from suppliers to customers only

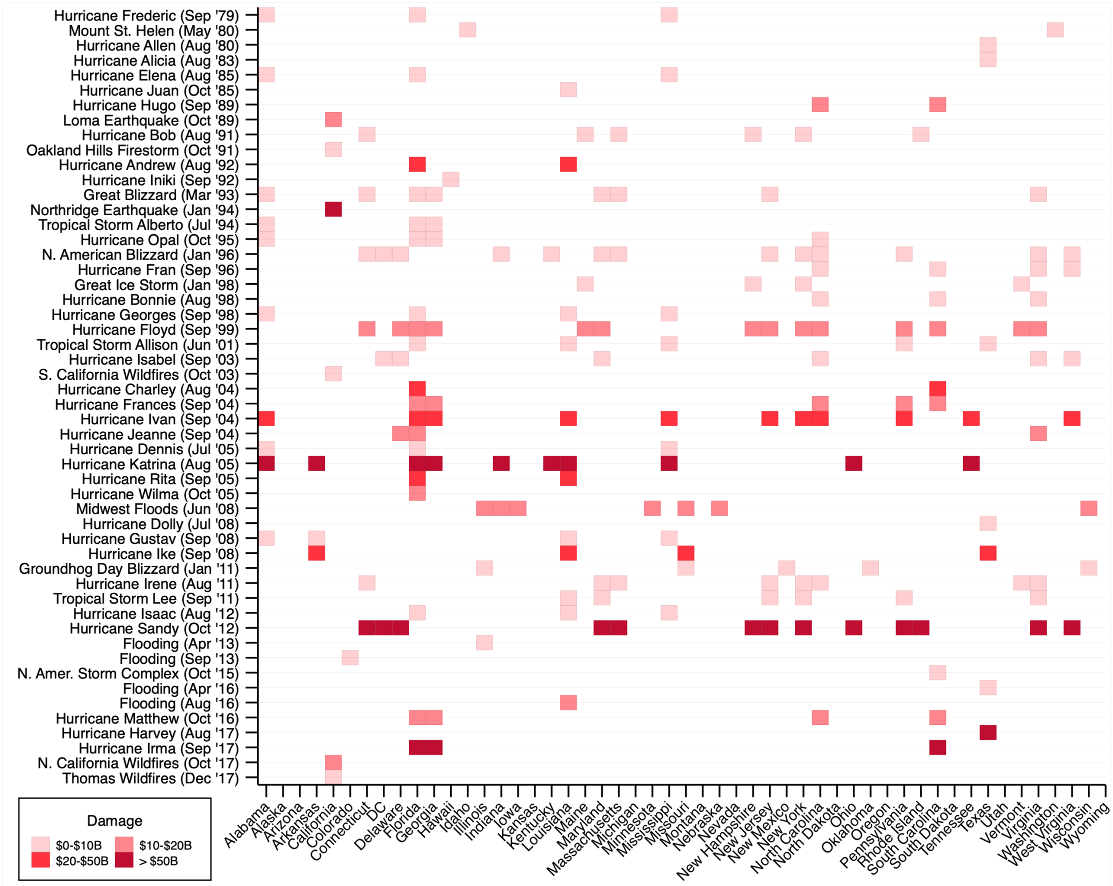

Figure 7: Major Natural Disasters by U.S. States (1978-2017)

Note: The figure shows all major natural disasters in the US between Jan 1978 and Dec 2017 and the states they affected. The damage reported is the total damage caused by a disaster (across all states) in 2017 US dollars.

when the supplier-customer relationship is active. The localized and short-term nature of the disasters, and the 300-kilometer exclusion zone around customers, suggest that it is not general equilibrium (demand-side) effects driving customer sales growth but rather supply-side effects.

While the majority of natural disasters occur along the southeast coast of the US (Figure 6), firms in our sample are dispersed across the country (Figure 2). Hence our sample includes a range of firms, from those located in disaster-free counties to those that are frequently disrupted by disasters. A substantial proportion of inter-state customer-supplier links (Figure 4) also allow us to study the propagation of supplier shocks to customers that are not directly affected by natural disasters.

2.5 Summary Statistics

Table 1 presents summary statistics for the sample of firms used. Panel A describes the supplier sample, which includes $\approx$ 5,000 firms generating $\approx$ 165,000 firm-quarter observations between 1978 and 2017. Firms are included in the supplier sample for all quarters from three years before being a supplier to at least one other firm, to three years after being last recorded. 'Eventually Treated' refers to firms hit by a major natural disaster at some point in the sample period, and 'Never Treated' refers to those which are not. The mean year-on-year quarterly sales growth for the supplier sample is $\approx$ 19%, although the median growth is only 4.7%, suggesting a long-tailed distribution. This value is similar across the treated and never treated groups. Firms record an average \$1.45 million of total assets and 4,800 employees. There is a 2% chance that a firm is hit by a natural disaster in any given quarter and a 1.4% chance that a disaster strikes a firm's customer in the sample.

Panel B presents the customer sample, comprising $\approx$ 2,000 firms and $\approx$ 91,000 customer-quarter observations. Firms are included in the sample for all quarters from three years before being first recorded as a customer to three years after being last recorded. 'Eventually Treated' refers to firms that, at some point over the sample period, have at least one supplier struck by a major natural disaster. 'Never Treated' refers to firms for which no suppliers are hit. There is an approximately equal split in the proportion of firms between the two groups. The primary variable of interest is *Sales growth*, the dependent variable in our regressions. The average sales growth for eventually treated and never treated firms is comparable, at approximately 9% and 12%, respectively. It appears that firm sales growth does not predict whether a disaster hits a supplier at any point.

From the mean values of firm *Total assets* and *number of employees*, larger firms are more likely to appear in the 'Eventually Treated' group. This is logical, as larger firms typically have more suppliers and are more likely to experience supply disruptions. We also observe that the average distance to suppliers is approximately equal for treated and untreated firms in the customer sample.

Table 1: Descriptive Statistics

Panel A: Supplier Sample	Never Treated			Eventually Treated			All		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Sales growth $(t-4, t)$	79,460	0.21	0.91	85,790	0.17	0.75	165,250	0.19	0.83
COGS growth $(t-4, t)$	78,254	0.22	0.91	84,794	0.18	0.77	163,048	0.20	0.84
Total assets (Mil. USD)	79,460	0.91	3.80	85,790	1.95	11.17	165,250	1.45	8.48
Return on assets	79,460	0.02	0.62	85,790	0.06	1.00	165,250	0.04	0.84
Number of employees ('000s)	77,300	3.82	12.13	84,275	5.72	18.96	161,575	4.81	16.09
Number of customers	79,460	1.00	1.16	85,790	1.15	1.28	165,250	1.08	1.23
Disaster hits firm itself (t)	79,460	0.00	0.00	85,790	0.04	0.19	165,250	0.02	0.14
Disaster hits customer (t)	79,460	0.01	0.11	85,790	0.02	0.12	165,250	0.01	0.12
Panel A: Customer Sample	Never Treated			Eventually Treated			All		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Sales growth $(t-4, t)$	47,982	0.12	0.43	42,959	0.09	0.32	90,941	0.11	0.38
COGS growth $(t-4, t)$	47,322	0.12	0.46	42,438	0.10	0.37	89,760	0.11	0.42
Total assets (Mil. USD)	47,982	2.74	5.91	42,959	14.60	39.93	90,941	8.35	28.40
Return on assets	47,982	0.10	0.29	42,959	0.14	0.15	90,941	0.12	0.23
Number of employees ('000s)	46,938	10.34	25.06	42,428	40.21	70.07	89,366	24.52	53.70
Number of suppliers	47,982	0.54	0.89	42,959	3.98	9.14	90,941	2.16	6.54
Disaster hits firm itself (t)	47,982	0.02	0.14	42,959	0.02	0.14	90,941	0.02	0.14
Disaster hits supplier (t)	47,982	0.00	0.00	42,959	0.04	0.19	90,941	0.02	0.13
Avg. distance to supplier ('000 km)	19,185	1.30	1.20	30,928	1.52	0.98	50,113	1.44	1.08

Notes: The table presents summary statistics for all supplier and customer firms. Firms are included for every quarter starting three years prior to when they first appear as a supplier (customer) and ending three years after they are last reported as a supplier (customer) in Compustat's *Customer Segment* dataset. Panel A presents the supplier sample comprising 5,121 distinct firms, creating 165,250 firm-quarter observations from 1978 to 2017. *Sales growth* and *COGS growth* report the firms' growth in sales and cost of goods sold, respectively, relative to the same quarter in the previous year. *Disaster hits firm* is a dummy variable taking a value of one if a major disaster hits the county of the firm's headquarters in quarter t, and zero otherwise. Panel B describes the customer sample. The sample includes 2,173 firms across 90,941 firm-quarter observations. The sample is divided into two groups. 'Eventually Treated' refers to those firms for which a natural disaster hit a supplier at any point in the sample period, and 'Never Treated' are those firms whose suppliers were never struck by a disaster.

On average, customer firms are located 1,520 km (1,300 km) from those of their suppliers in the eventually treated (never treated) sample. Hence, the geospatial distribution of suppliers between the two groups does not appear to be significantly different. 'Eventually treated' customers appear to be more slightly productive, with an average return on assets (ROA) of 14% compared to 10% for never-treated firms.

Finally, we observe that the incidence of 'Eventually Treated' and 'Never Treated' firms being hit by a major disaster is approximately equal, at 2%. The differences in size, ROA, and supplier count between eventually treated and never treated firms highlight the need to control for these variables.

3 Empirical model and results

We first examine the impact of natural disasters on (supplier) firms and the subsequent propagation of these supply shocks to their customers. We establish that natural disasters, plausibly exogenous events, negatively impact (supplier) firms' sales. We then show natural disasters induce a subsequent negative and significant impact on customer firms' sales growth, despite not being directly hit by the disaster. Finally, we evaluate how the transmission of these shocks differs based on the extent of customers' supply base diversity.

3.1 The direct and indirect effect of natural disasters

We begin by identifying exogenous supply disturbances that a) directly affect the supply operations of firms and b) indirectly disrupt the affected firms' customers. In line with Barrot and Sauvagnat (2016), we use major natural disasters in the US to establish both of these points.

There are numerous channels through which a natural disaster could conceivably disrupt a firm's production when hit by a natural disaster. For example, forced road closures, evacuation orders, downed power lines, damage to buildings, destruction of transportation infrastructure such as rail lines, damage to inventory, injuries, and loss of life could all result in a temporary contraction in firms' operations. For our purposes, we are not concerned with the specific mechanism by which a natural disaster affects a firm. It is sufficient for our strategy to show that natural disasters (random events) affect the production of diverse and non-diverse firms' suppliers equally, on average (see Section 3.4). This condition allows us to causally identify the effect of supply base diversification on the propagation of shocks.

We estimate the following difference-in-differences specifications to assess how natural disasters a) directly impact firms' quarterly sales growth and b) affect the sales growth of customer firms:

$$\Delta Sales_{i,t} = \alpha + \sum_{k=-4}^{9} \beta_k HitsFirm_{i,t-k} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t} \tag{1}$$

$$\Delta Sales_{i,t} = \alpha + \sum_{k=-4}^{9} \beta_k HitsFirm_{i,t-k} + \sum_{k=-4}^{9} \gamma_k HitsSupplier_{i,t-k} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t} \tag{2}$$

Equation (1) is estimated using the supplier sample. In equation (1), $\Delta Sales_{i,t}$ is growth in sales of firm i in quarter t, relative to the same quarter in the previous year. The indicator $HitsFirm_{i,t-k}$ takes the value of one when the county in which firm i is located is hit by a natural disaster at time $t+4$, $t+3, \ldots, t-9$. The coefficient, β_k, estimates the average change in sales growth (at time t) when a disaster directly hits a firm in period $t-k$. Variables τ_t and η_i represent year-quarter and firm fixed effects, respectively. Hence, we estimate the impact of natural disasters on firms' sales growth after purging out time and firm-specific effects. To account for potentially diverging trends amongst larger or more productive firms, we control for tercile indicators of firm size (assets) and return on assets (ROA), interacted with year-quarter dummies.[16] Finally, we also control for fiscal-quarter fixed effects.[17] All controls are not explicitly shown in equation (1) are represented by the vector $\mathbf{X}_{i,t}$.

Equation (2) estimates the propagation of shocks from affected suppliers to customer firms using the customer sample. The key regressor in equation (2) is $HitsSupplier_{i,t-k}$. $HitsSupplier_{i,t-k}$ takes a value of one if at least one supplier of the customer firm i was directly hit by a disaster in quarter $t-k$, and zero otherwise. The coefficient γ_k captures customer firms' average change in sales growth when a disaster hits at least one supplier in period $t-k$. While we exclude customer-supplier relationships located within 300 kilometers of

[16] We use the value of a firm's assets in the previous year to avoid misspecification, as damage from the disaster may distort the current value (Hsu et al., 2018).

[17] Year-quarter and fiscal quarter fixed effects are not perfectly collinear. For example, if firm A's fiscal year ends in December, and firm B's ends in June, the quarter from January to March is firm A's fiscal quarter 1, but firm B's fiscal quarter 3.

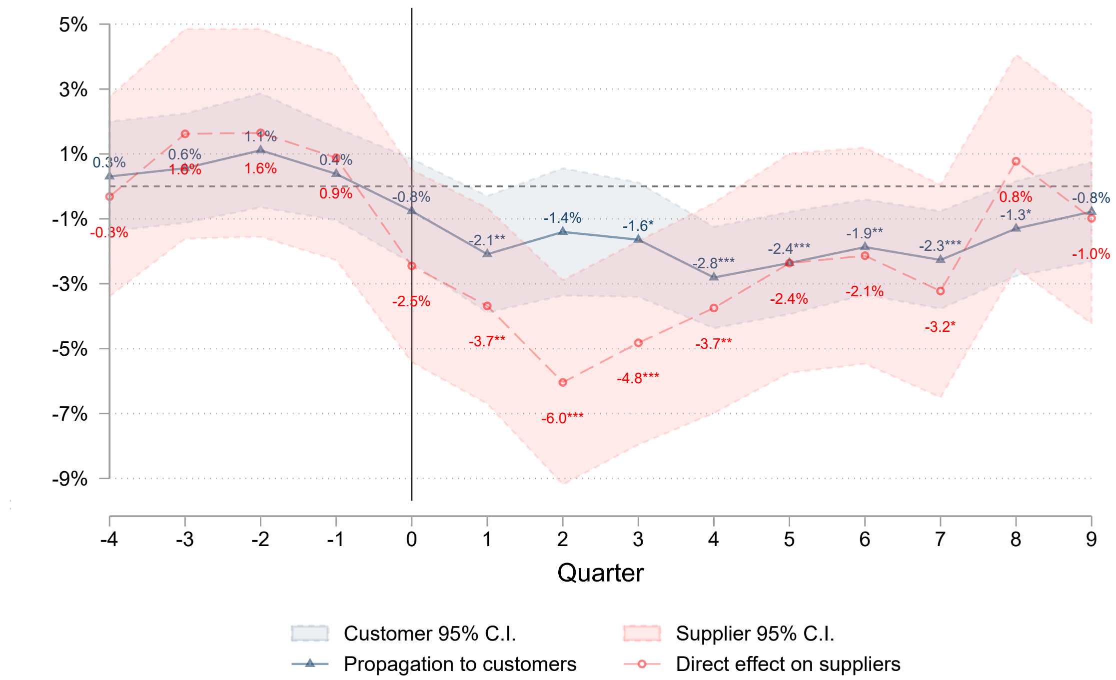

Figure 8: Propagation of Shocks From Suppliers to Customers

Note: This figure shows the average effect of natural disasters on firms' sales growth (dashed line) and the propagation of shocks to affected firms' customers (solid line). The dashed line shows β_k's from equation (1) together with 95% confidence bands. The solid line displays γ_k's from equation (2). Standard errors are clustered at the firm level.

each other, it is still possible that the customer is also simultaneously hit by the same (or some other) natural disaster.[18] To avoid confounding the effect of a supplier being hit by a natural disaster with the direct effect of the disaster on a customer firm, we also control for $HitsFirm_{i,t-k}$.

The size and ROA interactions with year-quarter dummies control for the possibility that larger firms may have more suppliers (and so are 'treated' more often) while also having heterogeneous trends in sales growth. In addition, $\mathbf{X}_{i,t}$ also controls for tercile indicators of the number of suppliers of firm c.[19] All other variables in equation (2) have the same interpretation as in equation (1). We cluster standard errors at the firm level in all regressions to control for serial correlation in errors.

Figure 8 summarizes the results. The dashed line shows the direct impact

[18] For example, Hurricane Katrina had tropical-storm-force winds extending 320 kilometers from its center (Reid, 2019).

[19] Consistent with Barrot and Sauvagnat (2016), we use a lagged supplier count in calculating the terciles of firms' number of suppliers.

of the disaster on firms (β_k's from equation (1)). As shown in the figure, firms experience a significant decline in sales growth after being hit by a natural disaster (dashed line), with the maximum decline (-6 pp) coming two quarters after the event. The seemingly delayed effect of a natural disaster on firm sales growth is consistent with what one might expect if disasters disrupt firms' production. Firms likely have excess inventory, which buffers the initial effects of reduced production on sales (Hendricks, Singhal and Zhang, 2009).[20] The estimates are economically significant as well; the mean (median) sales growth for the supplier sample is 19.2% (4.7%). The estimated 6.0 percentage points decrease in sales growth after two quarters thus represents approximately 31% decline in average sales growth. Exposure to a natural disaster lowers the sales growth of the affected firm by ≈3.7 percentage points after four quarters. Our results establish the negative impact of major natural disasters on firms directly affected by these supply shocks.

These economically large and idiosyncratic disruptions also have ramifications for the affected firms' customers, who are left unexpectedly without crucial inputs. The solid line in Figure 8 shows how the shocks propagate, from affected suppliers to their customers (γ_k's from equation (2)). The greatest impact on customer sales growth comes four quarters after a supplier is hit by a shock, with a 2.8 percentage points drop. This amounts to a 25% decline in average sales growth in the customer sample. Indirectly affected customers recover slowly, recovering pre-shock sales growth eight quarters after the initial shock. These results are economically significant as well, especially since purchases from a particular supplier represent, on average, only around 4% of a customer's cost of goods sold for a given quarter. Overall, there is clear evidence that supply shocks propagate from suppliers to customers. Additionally, our results align with existing literature on the topic.[21]

Figure 8 also shows that it is not pre-existing trends driving the change in customer sales growth but rather the effects of the shock. The dynamics of

[20] Furthermore, the sample only includes firms that report quarterly results at the *end* of a calendar quarter. Natural disasters are recorded for the calendar quarter in which they occur. Hence, on average, we expect that a firm has already registered half of its sales before being hit by a natural disaster (assuming that disaster timing is randomly distributed and firm sales are linearly distributed over the quarter).

[21] See Barrot and Sauvagnat, 2016 on the propagation of natural disaster shocks to US firms; Inoue and Todo, 2017 and Inoue and Todo, 2019 on the propagation of shocks under different network structures; and Carvalho et al., 2021 on the propagation of the shock from the Japanese Earthquake of 2011.

sales growth for customers and suppliers before and after the shock provide important insights. Supplier sales are worst affected after two quarters, remaining below average for four quarters following the disaster. On the other hand, customer sales are negatively affected four quarters after the disaster hits a supplier and stay below the average for a further three quarters. The impact of the shock on customer sales dissipates over a period of time as suppliers restore their production or customers establish alternative input sources. Furthermore, suppliers and customers likely have a level of inventory that counteracts and delays the impact of the shock.[22] Hence it would likely be several quarters before the supply shocks reduce customer firms' output.

Overall, there is clear evidence that natural disasters significantly disrupt suppliers' production and that these shocks propagate to customers through input-output linkages. Table D1 in Appendix D shows that the propagation of shocks from affected suppliers to customers occurs only when the customer-supplier relationship is active. Our results are robust to additional checks such as i) changing the number of lags of the key regressors in equations (1) and (2); ii) replacing sales growth with the cost of goods sold as the dependent variable (as discussed in Appendix D); and iii) changing the threshold (of 300 km) at which we exclude customer-supplier relationships. For brevity, we refer the reader to Barrot and Sauvagnat (2016) where they establish these baseline results.

3.2 Propagation of shocks and supply base diversity

In this section, we define three measures of supply base diversity, each of which is constructed using Compustat's *SALECS* variable. This variable reports the annual value of sales from a supplier to a customer, or conversely, the total purchases a customer makes from a given supplier in a year. All diversity measures vary at the customer-quarter level.[23] It is important to note that we estimate diversity based on firms' first-tier (as opposed to direct and indirect) suppliers since customers choose which firms to transact with. Furthermore, while businesses know their primary suppliers, they often have little or no knowledge of their second or higher-order suppliers

[22] Firms' production may also occur over months. For example, Boeing's A350 aircraft currently take three months to produce, from assembly to delivery (Airbus Press Office, 2018).

[23] To convert *SALECS* to a quarterly variable, we assume annual purchases are evenly distributed across all four quarters in a given year.

(Farrell and Newman, 2022). For this reason, we focus on diversity across firms' supply-base and abstract from more systemic measures that account for firms' entire supply chain. However, we consider this to be an important avenue for future work.[24]

Diversity Measures. We define three Herfindahl indexes that measure the degree of concentration of a firm's purchases over i) its suppliers, ii) industries, and iii) geographies in a given quarter. The first measure captures the extent to which a customer firm's total input purchases are dispersed across all its suppliers, irrespective of their industry or location. We refer to this as our *baseline* diversity measure. To classify firms as diverse according to this measure, we calculate a Herfindahl $\mathcal{H}_{i,t}$ for the customer firm i at quarter t as:

$$\mathcal{H}_{i,t} = \sum_{sup} \left\{ \frac{Purchases_{sup,t}}{Purchases_{i,t}} \right\}^2$$

where $Purchases_{sup,t}$ are firm i's purchases from supplier sup in quarter t. $Purchases_{i,t}$ are the total purchases by i in quarter t from suppliers $sup = 1,\ldots,N$. $\mathcal{H}_{i,t}$ takes a value between zero and one. Lower values of $\mathcal{H}_{i,t}$ indicate that the firm acquires inputs from a wide range of suppliers in less concentrated proportions. A firm with $\mathcal{H}_{i,t} = 1$ makes all its recorded purchases from a single supplier in quarter t. We define diverse firms using an indicator $Diverse^{\mathcal{H}}_{i,t}$ that takes the value one for firms in the lowest tercile of $\mathcal{H}$ over a quarter t. All other observations are assigned a value of zero. Hence $Diverse^{\mathcal{H}}_{i,t}$ varies both over firms and quarters.

Next, we measure the geographic diversity of a firm's supply base by computing a geographic Herfindahl $\mathcal{G}_{i,t}$, as:

$$\mathcal{G}_{i,t} = \sum_{st} \left\{ \frac{Purchases_{st,t}}{Purchases_{i,t}} \right\}^2$$

where $Purchases_{st,t}$ represents the value of purchases a customer makes from supplier(s) in state st and quarter t. If a customer firm has multiple suppliers located in the same state, $Purchases_{st,t}$ represents the total value of purchases from all the suppliers from that state. $Purchases_{i,t}$ is as defined earlier. Again, $\mathcal{G}_{i,t} \in (0\ 1]$ and lower values of $\mathcal{G}_{i,t}$ represent that i's input pur-

[24] See Elliott, Golub and Leduc (2022) who study the fragility of the entire supply network to idiosyncratic failures of individual supply relationships. Relatedly, see Carvalho, Elliott and Spray (2022) for a discussion on bottleneck firms.

chases are distributed across multiple states. A value $\mathcal{G}_{i,t} = 1$ implies that all of i's supplier(s) are from one state. We define firms in the lowest tercile of $\mathcal{G}$ in quarter t as geographically diverse and assign the indicator variable $Diverse^{\mathcal{G}}_{i,t} = 1$ for these firms. Non-diverse firms are assigned a value of zero.

Finally, we measure supply base diversity in terms of how i's total input purchases are dispersed over different industries. Here, we calculate the Herfindahl of a firm's purchases in quarter t by industry:

$$\mathcal{I}_{i,t} = \sum_{ind} \left\{ \frac{Purchases_{ind,t}}{Purchases_{i,t}} \right\}^2$$

where $Purchases_{ind,t}$ represents the total purchases from industry ind in quarter t. $Purchases_{i,t}$ is as defined above. Lower values of $\mathcal{I}_{i,t}$ indicate a more diverse supply base dispersed across various industries. A firm with $\mathcal{I}_{i,t} = 1$ acquires all its recorded inputs from a single industry. Here, we define firms in the lowest tercile of $\mathcal{I}$ as diverse across industries and assign the indicator $Diverse^{\mathcal{I}}_{i,t}$ a value of 1 for these firms. As with our other measures, we assign non-diverse firms a value $Diverse^{\mathcal{I}}_{i,t} = 0$.

Shock propagation and diversity. After creating the above three diversity measures, we test how supply shocks propagate from suppliers to customers when the customer firm is diverse relative to when it is not. To this end, we estimate the following model:

$$\begin{aligned} \Delta Sales_{i,t} &= \alpha + \beta HitsFirm_{i,t-4} + \gamma HitsSupplier_{i,t-4} + \delta DiverseFirm_{i,t} \\ &\quad + \kappa HitsSupplier_{i,t-4} \times DiverseFirm_{i,t} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

which is the same as equation (2) but with two additional variables. The variable $DiverseFirm_{i,t}$ represents one of the three diversity indicators. We run separate regressions for each firm diversity measure and omit the superscript for notational convenience. The interaction $HitsSupplier_{i,t-4} \times DiverseFirm_{i,t}$ takes a value 1 if a diverse firm's supplier is hit by a natural disaster. To keep the model tractable and parsimonious, we estimate equation (3) when the natural disaster hits the firm or its supplier at lag 4, when the indirect impact of natural disasters is the most pronounced.[25] The key coefficient of interest, κ, estimates the average marginal effect on the sales growth of a diverse firm when one of its suppliers is hit by a natural disaster.

[25]Similarly, Barrot and Sauvagnat (2016) estimate the impact of input specificity on customer sales when their suppliers are hit by a disaster at lag 4.

It is possible that our diversity indicators may be correlated with the size of the customer firms, i.e., larger firms have multiple suppliers. Our firm fixed effects, together with controls for firm size, ensure that coefficients on the diversity variables reflect the impact of customer diversity, not size. Controlling for the number of suppliers also ensures that our diversity measures capture how the customer's purchases are spread across suppliers and do not simply reflect the number of suppliers a customer has. Table 2 reports different versions of equation (3). We estimate the impact of customer diversity as measured by $Diverse^{\mathcal{H}}$, $Diverse^{\mathcal{G}}$, and $Diverse^{\mathcal{I}}$ in columns 1–2, 3–4, and 5–6, respectively. Columns 2, 4, and 6 report results with all possible controls as shown in equation (3).

A disaster hitting the customer firm reduces its sales growth by approximately two percentage points after four quarters. Across all specifications, the coefficient on the indicator *Diverse firm* is zero. Hence, diverse customers have similar sales growth as non-diverse customers.[26] The key difference is between the extent of propagation when a disaster hits one of the suppliers of a diverse customer vs. a non-diverse customer. Across all specifications, a disaster hitting a non-diverse customer's supplier reduces the customer's sales growth by $\approx$ 4-5 percentage points after four quarters. In contrast, the impact of a supply shock is approximately 70% smaller for diverse customers ($\hat{\gamma}+\hat{\kappa}$), irrespective of the definition of diversity used.

Columns (1) and (2) report regressions using the first measure of diversity, $Diverse^{\mathcal{H}}$. In column 2, with all controls, the estimated coefficient on *disaster hits one of diverse firm's supplier* $(t-4)$ is 0.029, significant at the 5% level. The drop in sales growth following a supplier being hit by a disaster is 2.9 percentage points lower for diverse firms. Where a non-diverse firm's sales growth drops by an average of 4.1 percentage points, a diverse firm's sales growth falls by a statistically insignificant 1.2 percentage points ($p-value\ = 0.07$). This result is economically significant, representing a 71% attenuation of the shock propagation. Recall that $Diverse^{\mathcal{H}}$ is derived from the Herfindahl of the value of a firm's purchases from suppliers in a given quarter. Hence it appears that having a more dispersed distribution of purchases across suppliers is beneficial to firms, as their reliance on any one supplier is reduced.

[26] Additionally, in Figure D1 in Appendix D we show that the median sales growth of diverse and non-diverse firms coincide for all three diversity measures across the entire sample period.

Table 2: Downstream Propagation - Customer Diversity

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.038***	0.029**	0.038***	0.030**	0.049***	0.037**
	[0.013]	[0.013]	[0.013]	[0.013]	[0.015]	[0.016]
Disaster hits one supplier $(t-4)$	-0.050***	-0.041***	-0.050***	-0.042***	-0.063***	-0.051***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.013]	[0.014]
Disaster hits firm $(t-4)$	-0.015	-0.018*	-0.015	-0.018*	-0.015	-0.018*
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.016*	-0.004	-0.020**	-0.009	-0.010*	-0.002
	[0.008]	[0.007]	[0.008]	[0.007]	[0.006]	[0.006]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	90,941	90,941	90,941	90,941	90,941	90,941
Adjusted R^2	0.209	0.227	0.209	0.227	0.209	0.227

Notes: This table presents estimates for the regression of firm sales growth, relative to the same quarter in the previous year, on dummies indicating if at least one of the firm's suppliers was hit by a disaster four quarters earlier, if the firm itself is diverse, and an interaction term of these two dummies. The regressions also include a dummy for whether the firm was hit by a natural disaster and an interaction term between this and the diversity dummy. The regression includes all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and a control variable for the number of suppliers a customer firm has. Columns (2), (4), and (6) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter. Standard errors, represented in square brackets, are clustered at the firm level.
*10%; **5%; ***1% significance levels.

The estimated coefficients on *disaster hits one of the diverse firm's suppliers* $(t-4)$ in columns (3) and (4) show that firms also benefit from a geographically dispersed supply network. Based on the specification with all controls in column 4, the temporary reduction in sales growth for geographically diverse firms is estimated to be 3 percentage points (significant at the 5% level) less than for their non-diverse counterparts.

The sales growth of geographically diverse firms falls by a statistically insignificant 1.2 percentage points ($p-value\ = 0.11$), compared to 4.2 percentage points for non-diverse firms. This amounts to a 71% reduction in the shock to firm sales growth caused by the disaster, highlighting the ability of firms with a geographically diverse supply base to attenuate supply shocks.

The results for regressions that use the industry diversity measure are similar. The estimated coefficients on the variable *disaster hits one of the diverse firm's suppliers* $(t-4)$ in columns 5 and 6 are again positive and significant. The estimate in column (6) is the largest from all three definitions of diversity, at 3.7 percentage points, significant at the 5% level. Firms identified as diverse according to industry dispersion experience a decline in sales growth of a statistically insignificant 1.4 percentage points ($p-value\ = 0.18$) following a supply chain shock, compared to 4 percentage points for non-diverse firms. This finding translates to 73% attenuation of the impact of the shock, another economically significant result. Our results suggest that firms that acquire inputs from a wide range of industries are more insulated against supply chain shocks. A caveat is that firms may not always be able to re-design products to use a wider array of inputs from more industries.[27] Nonetheless, it is encouraging to note that firms that use a diverse input mix are more robust to supply shocks relative to firms that rely heavily on inputs from fewer industries.

A valid concern is whether any single form of diversity drives the results. Expectedly, there is a degree of correlation between the three diversity measures. Our sample includes $\approx$ 24K observations where a firm has *at least* one of the three types of diversity considered. Of these, $\approx$ 40% of observations include all three types, and 56% have at least two of the three types of diversity. It is possible that only one or two forms of supply base diversity are

[27]Furthermore, it is possible that additional manufacturing complexity could increase production costs, potentially negating the benefits of reducing supply chain risk (Gabriel, 2013; Schwarz and Suedekum, 2014).

Table 3: Creation of New Links and the Destruction of Existing Links

	New links forming		Old links ending	
	(1)	(2)	(3)	(4)
County's number of disasters in the past five years	0.016**	-0.001	0.014**	-0.003
	[0.006]	[0.004]	[0.006]	[0.004]
Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes
Observations	80,066	80,066	80,066	80,066
Adjusted R^2	0.001	0.710	0.002	0.686

Notes: This table reports estimates for specifications (4) and (5). Specifically, columns 1 and 2 report estimates for equation (4), whereas columns 3 and 4 report estimates for equation (5). *10%; **5%; ***1% significance levels.

responsible for most of the attenuation effects observed. Nevertheless, 44% of 'diverse' firm-quarter observations include only one out of the three forms of diversity, and our estimates across the three specifications remain comparable in size and significance. Ostensibly, all three forms of supply base diversity imbue firms with benefits in attenuating supply shocks.

3.3 Are customer-supplier links endogenous to disasters?

In this section, we examine whether customers choose suppliers based on suppliers' vulnerability to natural disasters. In other words, we test whether proneness to natural disasters makes suppliers less attractive. If customer firms avoid suppliers in disaster-prone areas, this should go against finding any consequential propagation that we see in Figure 8 and Table 2. Nonetheless, we test whether the creation of new customer links or the destruction of existing connections is sensitive to the number of disasters the supplier's county experiences. To this end, we estimate the following specifications

$$\#\,New\ Links\ created_{county,t} = \#\,of\ disasters_{county,(t-5,\ t)} + \tau_t + \gamma_{county} + \varepsilon_{county,t} \quad (4)$$

$$\#\,New\ Links\ destroyed_{county,t} = \#\,of\ disasters_{county,(t-5,\ t)} + \tau_t + \gamma_{county} + \varepsilon_{county,t}. \quad (5)$$

Equations (4) and (5) have a unit of observation as a county-year. Equation (4) regresses the total number of new customer links formed by all firms headquartered in a *county* in year t on the total number of disasters experienced by that county in the past five years. Equation (5) regresses the total number of existing customers that all firms in a *county* lost in year t on the total number of disasters experienced by that county in the past five years. Both equations control for year and county fixed effects. As Table 3 shows, after controlling for the fixed effects, the number of disasters hitting a county does not explain the creation of new links or the destruction of existing links.

3.4 Are suppliers of diverse customers different?

It is important to consider any differential impact of natural disasters on the suppliers of diverse and non-diverse firms. Are suppliers of non-diverse firms systematically worse hit by natural disasters? Alternatively, do suppliers of diverse customers deal with natural disasters more effectively? If the answer to the above questions is yes, then any difference in the observed propagation may stem not from the diversity of the customer but from the heterogeneous impact of disasters on suppliers for diverse and non-diverse customers. Table 4 investigates this proposition, displaying estimates for the marginal effect of supplying to a 'diverse firm' on sales growth when hit by a disaster.

The table shows regression results over the supplier sample. We create an indicator variable that takes the value of one if at least one of the firm's customers in a given quarter is identified as diverse and zero otherwise. Using the supplier sample, we regress firm sales growth on i) an indicator that takes a value of one if a natural disaster hits the firm in any of the previous four quarters $(t-1)$ to $(t-4)$ and ii) the interaction of the disaster dummy with the diverse customer dummy. Columns 1, 3, and 5 include firm and year-quarter fixed effects. Columns 2, 4, and 6 also control for heterogeneous time trends based on firm size and return on assets. Under all three definitions of diversity, the coefficients on disaster hitting a firm with diverse customer(s) are statistically indifferent from zero. The estimates for the impact of a natural disaster, given by the coefficients in row 2, are consistent with estimates displayed in Figure 8. Overall, the impact of major natural disasters on firm sales growth appears to be orthogonal to the level of diversification of the affected firms' customer(s).

Table 4: Marginal Effect of Natural Disasters on Suppliers of Diverse Firms

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster hits firm with a diverse customer $(t-1, t-4)$	0.027	0.023	0.012	0.006	0.012	0.011
	[0.021]	[0.021]	[0.022]	[0.022]	[0.023]	[0.023]
Natural disaster hits firm $(t-1, t-4)$	-0.057***	-0.056***	-0.049***	-0.047***	-0.050***	-0.050***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.019]	[0.019]
Diverse firm	-0.051***	-0.048***	-0.055***	-0.051***	-0.058***	-0.055***
	[0.010]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	165,250	165,250	165,250	165,250	165,250	165,250
Adjusted R^2	0.149	0.158	0.149	0.158	0.150	0.158

Notes: This table shows results from estimating different versions of equation (1) but with two additional controls: *Diverse customer* and *Disaster hits firm with a diverse customer* $(t-1, t-4)$. *Diverse customer* is an indicator that takes a value of one if a supplier firm has at least one customer identified as diverse in quarter t. *Disaster hits firm with a diverse customer* $(t-1, t-4)$ is an indicator of disaster hitting the supplier firm anytime between $t-1$ to $t-4$, interacted with *Diverse customer* dummy. All columns report separate regressions. Columns 1–2, 3–4, and 5–6 report results where the customer's diversity is computed using our baseline, geography, and industry measures, respectively. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

3.5 Customer diversity and input specificity

Barrot and Sauvagnat (2016) find disaster-affected suppliers impose substantial output losses on their customers when the suppliers produce specific inputs. Barrot and Sauvagnat consider a supplier as specific if i) its industry lies above the median of the share of differentiated goods according to the classification provided by Rauch (1999), ii) its ratio of R&D expenses over sales is above the median in the two years before any given quarter, or iii) the number of patents it issued in the previous three years is above the median. They find customers' sales growth to decline by an additional 3-4 percentage points if a specific supplier is hit by a natural disaster relative to the disruption occurring to a non-specific supplier.

A valid concern is whether there is any systematic correlation between customers' supply base diversity and suppliers' input specificity. If diverse customers have non-specific suppliers in general, then the attenuation of supply shocks reported in Table 2 may not be attributed to supply base diversity but to the absence of specific inputs for such customers. In Table 5 we check how the results reported in Table 2 change if we control for input specificity.[28] Table 5 is mostly the same as Table 2; it reports different versions of equation (3) using the customer sample but with an additional indicator *Disaster hits specific supplier* $(t-4)$ that takes the value one if, for a customer firm, at least one specific supplier was affected by a natural disaster four quarters back. In addition, we control for an indicator *Specific supplier (Patent)* that takes the value one if a customer firm had at least one specific supplier at $t-4$. In Table 5, we define supplier specificity based on patents. Tables C1 and C2 in Appendix C report results when we use Rauch (1999) and R&D as measures of input specificity, respectively. The results are largely the same, irrespective of the measure of input specificity used.

The results show that supply base diversity and supplier input specificity are key drivers of how shocks propagate from suppliers to customers. Consistent with Table 2, Table 5 shows that: i) a disaster affecting a firm decreases its customers' sales growth by 3-4 percentage points after four quarters (row 3), and ii) having a diverse supply base attenuates supply shocks by approximately 3 percentage points (row 1). Finally, in line with Barrot and Sauvagnat (2016), input specificity does amplify supply shocks.

[28]We thank Julien Sauvagnat for sharing data on the three measures of input specificity. We merge our customer diversity variables with their data for the regressions reported in Table 5, which explains the lower number of observations relative to Table 2.

Table 5: Orthogonality of Supply Base Diversity and Input Specificity (Patent)

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.032**	0.029**	0.032***	0.029**	0.041***	0.032**
	[0.013]	[0.013]	[0.012]	[0.013]	[0.015]	[0.016]
Disaster hits specific supplier $(t-4)$	-0.031**	-0.031***	-0.030**	-0.031**	-0.030**	-0.030**
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Disaster hits one supplier $(t-4)$	-0.036***	-0.030***	-0.036***	-0.031***	-0.047***	-0.038***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.012]	[0.013]
Disaster hits firm $(t-4)$	-0.023**	-0.024**	-0.023**	-0.024**	-0.023**	-0.024**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.012	-0.002	-0.014*	-0.005	-0.004	0.002
	[0.008]	[0.008]	[0.008]	[0.008]	[0.006]	[0.006]
Specific supplier (Patent)	-0.013**	-0.007	-0.013*	-0.007	-0.013**	-0.007
	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]	[0.007]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	73,377	73,377	73,377	73,377	73,377	73,377
Adjusted R^2	0.212	0.232	0.213	0.232	0.212	0.232

Notes: This table presents estimates for specification (3), but with the inclusion of a dummy that indicates whether the firm has a specific supplier (as measured by the number of patents) and an interaction between this *specificity* dummy and *disaster hits supplier*. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and a control variable for the number of suppliers a customer firm has. Columns (2), (4), and (6) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter. Standard errors, represented in square brackets, are clustered at the firm level.* p<0.1; ** p<0.05; *** p<0.01.

If a specific supplier is hit with a disaster, its customers experience an additional 3 percentage points decline in sales growth after four quarters. The amplification of supply shocks due to input specificity is consistent with Barrot and Sauvagnat (2016). Overall, both supply base diversity and input specificity significantly affect how shocks transmit from suppliers to customers. While suppliers' input specificity amplifies the transmission, customers' supply base diversity attenuates it.

3.6 Other robustness tests

Additional controls. We test whether our findings in Table 2 are robust to the inclusion of extra controls. Figure C1 in Appendix C presents estimates for specification (3) but with the progressive inclusion of firm, time, size, return on assets (ROA) by quarter, state-time, and industry by quarter fixed effects. Each specification shown in the figure adds additional control(s) to the previous regression. For example, the regression represented by the small square marker (first in each panel) is the same as equation (3), though it only includes firm and time fixed effects. The following specification (represented by the large triangle marker) includes firm and time fixed effects as well as size and ROA-time fixed effects.

The coefficients on *Disaster hits supplier of a non-diverse firm* $(t-4)$ have the same interpretation as in Table 2 and capture the effect on non-diverse firms' sales growth when a supplier is hit with a disaster four quarters back. Across all specifications, non-diverse firms experience a statistically significant reduction in sales growth of around 4 percentage points. *Disaster hits supplier of a diverse firm* $(t-4)$ captures the corresponding effect of a supplier shock on diverse firms' sales growth.[29]

We find that diverse firms only experience a decline in sales growth of approximately 1-2 percentage points, though this effect is statistically insignificant across most specifications. In summary, our key empirical finding that diverse firms mitigate the impact of adverse supply shocks is robust to the inclusion of the controls shown in Figure C1.

Finally, firms with a higher inventory-to-sales ratio may be more insulated when a supplier is disrupted since these firms can maintain production

[29]In Table 2, the coefficient on *Disaster hits supplier of a diverse firm* $(t-4)$ measures the *benefit* of having a diverse supply base, whereas in Figure C1 we show the *overall* effect of a supply shock on diverse firms' sales growth (i.e., $(\hat{\gamma}+\hat{\kappa})$ in equation (3)).

at normal levels. Importantly, if diverse firms tend to carry greater inventory, then the benefits of diversification may be overestimated and explained by these firms' operational slack. We test for this in the final specification of Figure C1. Our results are robust to the inclusion of this variable in our specification. Notably, diverse firms' sales growth is not statistically different from zero when a supplier is struck with a disaster. In contrast, non-diverse firms' sales growth declines by approximately 4 percentage points. This result holds for all three types of diversity.

Firm characteristics and diversity. We also check if the supply base diversity of a firm is correlated with any other firm characteristic that may also affect the propagation of shocks from its suppliers. Figure C2 in Appendix C shows how each diversity measure is correlated with different firm attributes. Specifically, we regress each diversity indicator on a different firm characteristic and all controls that are included in Table 2. The figure shows that all three diversity measures are orthogonal to important firm attributes. Firstly, firms with many employees could potentially have the personnel to manage supply chain disruptions better, thus mitigating the effects of adverse shocks. However, we do not find any significant correlation between firms' number of employees and each of our diversity measures. Second, *Inventory* is a dummy variable representing the tercile of a given firm's inventory-to-sales ratio for its respective industry. Firms with greater inventory may be more risk-averse and choose a broader range of suppliers. However, we again do not find firms' inventory level to be a significant predictor of diversity.

R&D expenses is a tercile dummy of firms' ratio of R&D expenditure to sales in each industry. This gives the number of R&D dollars spent for every dollar of sales achieved. It is plausible that firms that invest more in R&D also invest more in supply chain management. We find no significant correlation between R&D expenses and any of the diversity indicators. Next, *SG&A expenditure* is the ratio of a firm's Selling, General, and Administrative spending to its total quarterly sales, again computed as a tercile dummy by industry. We include this variable because firms that spend more on administration systems may be better prepared for operational disruptions. Again, SG&A spending does not appear to be a statistically significant predictor of firm diversity.

Finally, we consider a firm's property, plant, and equipment expenditure relative to its total assets (represented by *PP&E expenditure*, which is also an industry-tercile dummy). It is conceivable that firms with higher PP&E expenditure values have more capital-intensive production and are more exposed to supply shocks. If these firms simultaneously purchase from more suppliers (and so are more 'diverse'), this would cause the estimates from Table 2 to overstate the effect of diversity. However, PP&E is also not correlated with each diversity indicator. Notably, while all firm characteristics (except the number of employees) are dummy variables in Figure C2, our results hold for continuous versions of these variables.

Continuous diversity measures. Finally, we test whether our results are robust to the inclusion of continuous diversity measures. Table C3 in Appendix C presents estimates of equation (3) but where *Diverse* is a continuous variable instead of a tercile indicator. Across the three diversity measures, the coefficient on *Disaster hits one of a diverse firm's suppliers* $(t-4)$ implies that at the mean level of diversity, supplier shocks are attenuated by ≈ 1.7 to 2.6 percentage points, which is consistent with our estimates in Table 2.

4 Quantitative Application

Our results in the previous section provide evidence that supply base diversification significantly mitigates the propagation of natural disaster shocks from suppliers to direct customers. However, our reduced-form estimates are inadequate for quantifying the impact of supply base diversification on real GDP since firms' sales comprise both intermediate and final sales. In this section, we build a general equilibrium model of production networks in the spirit of Acemoglu et al. (2012) and Baqaee and Farhi (2019) to estimate the macroeconomic benefit of supply base diversification, which we define as the increase in real GDP due to substitution between inputs by diverse firms. We estimate diverse firms' elasticity of substitution to be close to two over a one-year time horizon, implying these firms exhibit a moderate degree of substitutability between inputs. In contrast, non-diverse firms have an elasticity of around one. We then use the model to quantify how substitution by diverse firms impacts final demand in response to the largest natural disasters in our sample.

4.1 Environment and Equilibrium

We define a set of firms $\mathcal{S}$, a set of *diverse* firms $\mathcal{D}$ and a set of *non-diverse* firms $\mathcal{N}$, where $\mathcal{D} \subseteq \mathcal{S}$, $\mathcal{N} \subseteq \mathcal{S}$ and $\mathcal{D} = \mathcal{S} - \mathcal{N}$. There are N firms in the economy, $N_{\mathcal{D}}$ diverse firms and $N_{\mathcal{N}}$ non-diverse firms, where $N_{\mathcal{D}} + N_{\mathcal{N}} = N$. A firm is classified as diverse if it satisfies at least one of the definitions of diversity outlined in Section 3.2. Each firm in the economy produces one distinct good.

Households. There is a representative household that consumes the output of firms and has Cobb-Douglas preferences over final consumption. The household derives income by supplying capital K inelastically to firms.

The household's problem is

$$\max_{\{c_i\}_{i \in S}} \quad \mathcal{U} = \prod_{i \in S} c_i^{a_i} \quad \text{subject to} \quad I = \sum_{i \in S} p_i c_i.$$

where I is total income, c_i is final demand for good $i \in S$, p_i is the price of good i, and a_i is the consumption share of good i in the household's bundle where $\sum_{i \in \mathcal{S}} a_i = 1$.

Real GDP. We define changes in real GDP using the Divisia index

$$d \log Y = \sum_{i \in \mathcal{S}} b_i d \log c_i,$$

where $b_i \equiv \frac{p_i c_i}{\sum_{j \in \mathcal{S}} p_j c_j}$ is the final expenditure share of good i. The Divisia index for real GDP correctly measures changes in welfare in our model since we assume the existence of a representative consumer.

Production. Good $i \in S$ is produced via a constant-returns CES production function of the form

$$y_i = \left(\mu_i^{\frac{1}{\theta_s}} (z_i k_i)^{\frac{\theta_s - 1}{\theta_s}} + \sum_{j \in \mathcal{S}} \omega_{ij}^{\frac{1}{\theta_s}} x_{ij}^{\frac{\theta_s - 1}{\theta_s}} \right)^{\frac{\theta_s}{\theta_s - 1}}$$

where y_i is total output, z_i is a capital-augmenting shock, k_i is capital use, and x_{ij} is the quantity of j's product used by i. The parameters μ_i and $\{\omega_{ij}\}_{j \in \mathcal{S}}$ capture the intensity with which capital and intermediates from firm $j \in \mathcal{S}$ are used by i, respectively. Finally, θ_s is the elasticity of substitution for firm

i in set $s \in (\mathcal{D}, \mathcal{N})$. For example, if firm i is classified as diverse, then $s = \mathcal{D}$ and firm i has elasticity of substitution $\theta_{\mathcal{D}}$.

Firms maximize profits given by

$$\max_{k_i, \{x_{ij}\}_{j \in S}} \pi_i = p_i y_i - r k_i - \sum_{j \in S} p_j x_{ij}.$$

where r is the rental price of capital. The market-clearing condition for good $i \in \mathcal{S}$ is

$$y_i = c_i + \sum_{j \in \mathcal{D}} x_{ji} + \sum_{j \in \mathcal{N}} x_{ji}. \tag{6}$$

Similarly, market-clearing for capital is given by $K = \sum_{i \in S} k_i$.

Equilibrium. The competitive equilibrium is defined in the usual way, where all producers maximize profits taking prices as given, the household maximizes its utility subject to its budget constraint, and the markets for goods and capital clear.

Shocks. In line with Carvalho et al. (2021), we model natural disasters as capital-augmenting shocks $d \log z_i \leq 0$ that result in the reduction of disaster-affected firms' operable capital. We assume that firms in the economy are not subject to any other shock.

4.2 Input-Output Definitions

Before discussing our theoretical results, we introduce some input-output notation and definitions. In particular, we define the economy's input-output and Leontief inverse matrices, Domar weights, and capital expenditure shares, all of which are measured at the initial (pre-shock) equilibrium.

Input-output matrices. Let $\mathbf{\Omega}_{\mathcal{D}}$ be the $N \times N$ *diverse* input-output matrix, whose ij^{th} element is equal to i's expenditure on intermediates from j:

$$\Omega_{ij}^{\mathcal{D}} \equiv \frac{p_j x_{ij}}{p_i y_i} \quad i \in \mathcal{D}, \ j \in \mathcal{S}.$$

The first $N_{\mathcal{D}}$ rows of $\mathbf{\Omega}_{\mathcal{D}}$ correspond to the intermediate input shares of the economy's diverse firms, and the last $N_{\mathcal{N}}$ rows are zeros because these elements correspond to non-diverse customers.

Similarly, let $\mathbf{\Omega}_{\mathcal{N}}$ be the economy's $N \times N$ *non-diverse* input-output matrix with typical element

$$\Omega_{ij}^{\mathcal{N}} \equiv \frac{p_j x_{ij}}{p_i y_i} \quad i \in \mathcal{N}, \;\; j \in \mathcal{S}.$$

The last $N_{\mathcal{N}}$ rows of $\mathbf{\Omega}_{\mathcal{N}}$ contain the intermediate input shares of the economy's non-diverse customers, and the first $N_{\mathcal{D}}$ rows are zeros (since these relate to diverse customers).

Finally, the economy's *complete* input-output matrix $\mathbf{\Omega}$ is given by

$$\mathbf{\Omega} = \mathbf{\Omega}_{\mathcal{D}} + \mathbf{\Omega}_{\mathcal{N}}$$

where the ij^{th} element of $\mathbf{\Omega}$ captures the direct exposure from firm $j \in \mathcal{S}$ to firm $i \in \mathcal{S}$ in terms of revenues/costs (see Carvalho and Tahbaz-Salehi, 2019; Baqaee and Farhi, 2019, and Baqaee and Farhi, 2020, for a more detailed discussion of the input-output matrix). The matrix $\mathbf{\Omega}$ contains all direct linkages between firms in the economy and is a standard concept in the literature on production networks.

Leontief inverse. Associated with the economy's complete input-output matrix $\mathbf{\Omega}$ is the $N \times N$ Leontief inverse matrix, defined

$$\mathbf{\Psi} \equiv (I - \mathbf{\Omega})^{-1} = I + \mathbf{\Omega} + \mathbf{\Omega}^2 + \ldots$$

The ij^{th} element of the Leontief inverse $\mathbf{\Psi}$ records all direct and indirect ways through which firm $i \in \mathcal{S}$ uses inputs from $j \in \mathcal{S}$. In particular, $(\mathbf{\Omega}^n)_{ij}$ measures the weighted sum of all paths of length n linking firm j to firm i through the production network. The Leontief inverse is related to the notion of *influence* in Acemoglu et al. (2012), capturing the systemic importance of any given production unit.

Domar weights. Let $\boldsymbol{\lambda}_{\mathcal{D}}$ be the $N \times 1$ vector of Domar weights for diverse firms, with typical element $\lambda_i^{\mathcal{D}}$ defined as the total revenue of firm $i \in \mathcal{D}$, as a fraction nominal GDP. Formally,

$$\lambda_i^{\mathcal{D}} = \frac{p_i y_i}{\text{GDP}} \quad i \in \mathcal{D}.$$

As with diverse input-output matrix, the first $N_{\mathcal{D}}$ rows of $\boldsymbol{\lambda}_{\mathcal{D}}$ are, in general, nonzero and correspond to the Domar weights of diverse customers. The last

$N_{\mathcal{N}}$ rows relate to non-diverse firms and are identically equal to zero. Similarly, the $N \times 1$ vector $\boldsymbol{\lambda}_{\mathcal{N}}$ contains Domar weights for non-diverse customers in its last $N_{\mathcal{N}}$ rows. The first $N_{\mathcal{D}}$ rows of $\boldsymbol{\lambda}_{\mathcal{N}}$ are zeros. A generic element of $\boldsymbol{\lambda}_{\mathcal{N}}$ is given by

$$\lambda_i^{\mathcal{N}} = \frac{p_i y_i}{\text{GDP}} \quad i \in \mathcal{N},$$

Furthermore, the vector of Domar weights for all the firms in the economy is defined as

$$\boldsymbol{\lambda} = \boldsymbol{\lambda}_{\mathcal{D}} + \boldsymbol{\lambda}_{\mathcal{N}}.$$

Intuitively, Domar weights capture all direct and indirect exposures of a given firm to final demand.[30]

Capital expenditure shares. Lastly, we define the $N \times 1$ vector of capital expenditure shares $\boldsymbol{\eta}$ with i^{th} element given by the expenditure of firm $i \in \mathcal{S}$ on capital, as a fraction of nominal GDP,

$$\eta_i = \frac{rk_i}{\text{GDP}} \quad i \in \mathcal{S},$$

where $\sum_{i \in \mathcal{S}} \eta_i = 1$. Capital expenditure shares measure the intensity of a given firm's direct reliance on capital. As we will see in the next subsection, capital expenditure shares (and changes in capital shares) are sufficient statistics for characterizing the impact of natural disasters on real GDP. We are now in a position to introduce our theoretical results.

4.3 Theoretical Results

Propagation over the network. Our first result characterizes how a capital-augmenting shock to firm j propagates over the production network and shapes firm i's sales share. In this sense, the production network endogenously responds to firm-level shocks. In particular, we provide an expression that is jointly linear in the elasticities $(\theta_{\mathcal{D}}, \theta_{\mathcal{N}})$, allowing us to estimate these

[30] From the goods market-clearing condition given by equation (6), we can write $\lambda_i = b_i + \sum_{j \in \mathcal{S}} \lambda_j \Omega_{ji}$ by multiplying both sides by $p_i \cdot \text{GDP}^{-1}$. Writing this new equation in matrix form and solving for the vector of Domar weights, we get $\boldsymbol{\lambda}' = \mathbf{b}'\boldsymbol{\Psi}$. This expression for $\boldsymbol{\lambda}$ shows that the economy's Domar weights are a function of the Leontief inverse and final expenditure shares. In this respect, the Domar weight of firm i captures all direct and indirect paths through which the household sector is linked to i.

parameters by linear regression. Anticipating the results of the following subsection, diverse firms are characterized by an elasticity of substitution greater than one ($\theta_{\mathcal{D}} > 1$), implying gross substitutability among inputs for diverse firms. In contrast, non-diverse firms have an elasticity of substitution that is less than one ($\theta_{\mathcal{N}} < 1$), implying the inputs of non-diverse firms are gross complements.

Proposition 1. *The impact of a capital-augmenting shock to firm j on firm i's Domar weight is given by*

$$\frac{d\log\lambda_i}{d\log z_j} = \overbrace{(\theta_{\mathcal{D}}-1)\frac{\eta_j}{\lambda_i\lambda_j}\sum_{k\in\mathcal{D}}\sum_{m\in\mathcal{S}}\Omega_{km}\lambda_k\Psi_{mi}\left(\Psi_{mj}-\Psi_{kj}\right)}^{\text{Demand effect of diverse firms}} + \underbrace{(\theta_{\mathcal{N}}-1)\frac{\eta_j}{\lambda_i\lambda_j}\sum_{k\in\mathcal{N}}\sum_{m\in\mathcal{S}}\Omega_{km}\lambda_k\Psi_{mi}\left(\Psi_{mj}-\Psi_{kj}\right)}_{\text{Demand effect of non-diverse firms}}. \quad (7)$$

Proof. See Appendix A.

The result, which will serve as the basis of our quantitative analysis of the subsequent section, highlights the role of the economy's production network (as captured by the matrices $\boldsymbol{\Omega}$ and $\boldsymbol{\Psi}$) in the propagation of natural disaster shocks. Specifically, a disturbance to firm j induces its direct and indirect customers to change the composition of their expenditure on various inputs, thus resulting in a change in demand for firm i's output. The first set of summands on the right-hand side of equation (7) captures how substitution between inputs by *diverse* firms ($k \in \mathcal{D}$) shapes i's sales share in response to a capital-augmenting shock to firm j. The term $(\Psi_{mj} - \Psi_{kj})$ suggests that in response to a negative shock, a diverse firm k (who is a direct or an indirect customer of j) substitutes its reliance on j towards other firms in the economy ($m \in \mathcal{S}$). The extent of substitution depends on the difference between k's and m's overall reliance on the disrupted firm j.[31] In other words, the diverse firm substitutes expenditure towards those inputs that are relatively less exposed to the shock. Naturally, the extent of substitution depends on the relative expenditure of k on firm m's output (Ω_{km}). Additionally, substitution towards the input produced by m increases the sales share of firm i in proportion to

[31] If k is not reliant on j at all, i.e., if $\Psi_{kj} = 0$, then there will be no demand effect on firm i from firm k. This is because if $\Psi_{kj} = 0$, then either of Ψ_{mj} or Ω_{km} is necessarily equal to zero.

m's overall exposure to i (as captured by Ψ_{mi}). The overall demand effect is increasing in j's sensitivity to natural disasters or j's expenditure on capital as a fraction of its sales (η_j/λ_j) and the size of diverse firm k relative to i (λ_k/λ_i).[32] Therefore, the overall change in i's Domar weight depends crucially upon the relative exposure of diverse firms' suppliers to the shock and the elasticity of substitution $\theta_{\mathcal{D}}$.

By contrast, a non-diverse firm $k \in \mathcal{N}$ (for which inputs are gross complements $\theta_{\mathcal{N}} < 1$) demands *more* input from m if m is relatively more exposed to the shock than k (as measured by $\Psi_{mj} - \Psi_{kj}$). Due to complementarity in production, k decreases expenditure on inputs that are relatively less exposed to the shock. Like before, this effect increases with m's expenditure share in k's production (Ω_{km}), the size of the non-diverse firm relative to i (λ_k/λ_i), and j's sensitivity to disasters (or the level of capital intensity, η_j/λ_j).[33] Finally, the effect is stronger as the degree of complementarity (for non-diverse firms) increases (as $\theta_{\mathcal{N}}$ approaches zero).

The macroeconomic impact of natural disasters. Our main objective is to use our model to measure the macroeconomic benefit of supply base diversification. However, we must first characterize how natural disaster shocks affect real GDP by propagating through the network, affecting final demand. To a first-order of approximation, the effect of a firm-level capital-augmenting shock on aggregate output is sufficiently summarized by the firm's capital expenditure share.[34] Details of the underlying network structure and elasticities of substitution are not required to compute the first-order approximation. However, substitution by firms across inputs plays a role in shaping aggregate output to the second-order of approximation (Baqaee and Farhi, 2019). For example, the substitution patterns of diverse firms can substantially mitigate the negative effect of natural disasters on real GDP by reorienting expenditures towards less-affected producers. Therefore, to measure the macroeconomic benefits of diversity, we

[32] Changes in relative prices induce diverse firms to substitute across inputs. This can be seen by noting that $\frac{d\log p_m}{d\log z_j} = -\Psi_{mj}\frac{\eta_j}{\lambda_j}$. The more exposed is firm m to the shock, the greater the increase in its price.

[33] See Baqaee and Farhi (2019) and Baqaee and Farhi (2020) for a more general treatment of the relationship between elasticities of substitution and propagation effects through the production network.

[34] We show this in the proof of Proposition 2 in Appendix A. This result is in contrast to Hulten (1978) where Domar weights are sufficient statistics characterizing the first-order impact of Hicks-neutral productivity shocks on GDP.

must first understand how real GDP depends upon the elasticities $(\theta_{\mathcal{D}}, \theta_{\mathcal{N}})$. Proposition 2 shows how changes in firms' capital expenditure shares are sufficient to summarize how shocks affect GDP to the second-order of approximation.

Proposition 2. *The second-order impact of capital-augmenting microeconomic shocks on real GDP is given by*

$$\frac{d^2 \log Y}{d \log z_j d \log z_i} = \frac{d\eta_i}{d \log z_j} = (1-\theta_s)\left[\eta_i \Psi_{ij}\frac{\eta_j}{\lambda_j} - \mathbf{1}(i=j)\right] + \eta_i \frac{d\log\lambda_i}{d\log z_j} \tag{8}$$

where θ_s is the elasticity of substitution of firm $i \in \mathcal{S}$, and $\mathbf{1}(i=j)$ is the j^{th} unit vector.

Proof. See Appendix A.

To provide the intuition behind equation (8), consider the economy shown in Figure 9. In this economy, firm i is purely downstream from all other firms, such that $\Omega_{mi} = \Psi_{mi} = 0$ for all $m \in \mathcal{S}$. This implies $\frac{d\log\lambda_i}{d\log z_j} = 0$, which is an immediate consequence of equation (7). Furthermore, assume firm i is diverse with elasticity of substitution $\theta_{\mathcal{D}} > 1$. The negative shock to j causes i to reduce demand expenditure on j while increasing its spending on capital and intermediates from other suppliers. Specifically, firm i substitutes towards those input suppliers that are less exposed to the shock to j than i itself (Proposition 1), increasing the sales share of these less-exposed producers. Ultimately, this substitution behavior by i has a positive impact on aggregate output to a second order. While the aggregate output declines due to a shock to j, it declines to a lesser extent due to the substitution behavior of diverse firms in the economy.

4.4 Model Estimation

In this subsection, we use the Compustat data and sector-level input-output data from the BEA to estimate the elasticities of substitution for diverse and non-diverse firms $(\theta_{\mathcal{D}}, \theta_{\mathcal{N}})$. These estimates are essential to our aggregation exercise of the following subsection.

First, note that equation (7) expresses the change in any given firm's sales as a function of the elasticities of substitution and production network para-

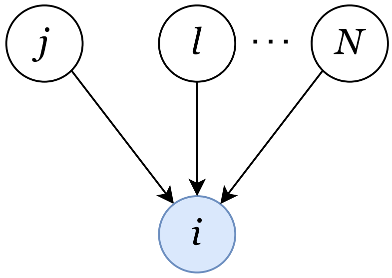

Figure 9: Example Network

Note: The blue node represents a diverse firm, whereas white nodes represent firms that could either be diverse or non-diverse. Directed arrows depict the flow of intermediate inputs between firms.

meters. Therefore, using the EM-DAT natural disaster data in conjunction with the Compustat data on supplier-customer relationships and firm-level sales, equation (7) provides us with a natural starting point for estimating the model. In response to a vector of shocks $\Delta \log \mathbf{z}$, equation (7) can be written in matrix form and in terms of discrete changes in Domar weights as

$$\Delta \log \boldsymbol{\lambda} = (\theta_{\mathcal{D}} - 1) \underbrace{\mathrm{diag}(\boldsymbol{\lambda})^{-1} \boldsymbol{\Psi}' \left(\Delta \log \mathbf{z} \circ \mathbf{M} \cdot \boldsymbol{\Omega}'_{\mathcal{D}} - \boldsymbol{\Omega}'_{\mathcal{D}} \cdot \Delta \log \mathbf{z} \circ \mathbf{M}\right) \boldsymbol{\lambda}_{\mathcal{D}}}_{\textit{Diverse}}$$
$$+ (\theta_{\mathcal{N}} - 1) \underbrace{\mathrm{diag}(\boldsymbol{\lambda})^{-1} \boldsymbol{\Psi}' \left(\Delta \log \mathbf{z} \circ \mathbf{M} \cdot \boldsymbol{\Omega}'_{\mathcal{N}} - \boldsymbol{\Omega}'_{\mathcal{N}} \cdot \Delta \log \mathbf{z} \circ \mathbf{M}\right) \boldsymbol{\lambda}_{\mathcal{N}}}_{\textit{Non-diverse}}$$

where $\Delta \log \boldsymbol{\lambda}$ is an $N \times 1$ vector and $\boldsymbol{\lambda}$, $\boldsymbol{\lambda}_{\mathcal{D}}$, $\boldsymbol{\lambda}_{\mathcal{N}}$, $\boldsymbol{\Omega}_{\mathcal{D}}$, $\boldsymbol{\Omega}_{\mathcal{N}}$, and $\boldsymbol{\Psi}$ are as defined in Section 4.2. Finally, $\mathbf{M}$ is an $N \times N$ matrix that appropriately weights the shock vector $\Delta \log \mathbf{z}$ (see the proof of Proposition 1 in Appendix A for an exact definition of $\mathbf{M}$).

The above equation is jointly linear in $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$, permitting the estimation of the model by linear regression. Denoting by $\textit{Diverse}_i$ and $\textit{Non-diverse}_i$ the i^{th} element of vectors $\mathrm{diag}(\boldsymbol{\lambda})^{-1} \boldsymbol{\Psi}' \left(\Delta \log \mathbf{z} \circ \mathbf{M} \cdot \boldsymbol{\Omega}'_{\mathcal{D}} - \boldsymbol{\Omega}'_{\mathcal{D}} \cdot \Delta \log \mathbf{z} \circ \mathbf{M}\right) \boldsymbol{\lambda}_{\mathcal{D}}$ and $\mathrm{diag}(\boldsymbol{\lambda})^{-1} \boldsymbol{\Psi}' \left(\Delta \log \mathbf{z} \circ \mathbf{M} \cdot \boldsymbol{\Omega}'_{\mathcal{N}} - \boldsymbol{\Omega}'_{\mathcal{N}} \cdot \Delta \log \mathbf{z} \circ \mathbf{M}\right) \boldsymbol{\lambda}_{\mathcal{N}}$, respectively, we can estimate the elasticities of substitution $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ via the following specification:

$$\Delta \log \lambda_{it} = \gamma_i + \gamma_t + \beta_1 * \textit{Diverse}_{it} + \beta_2 * \textit{Non-diverse}_{it} + \varepsilon_{it} \tag{9}$$

where $\theta_{\mathcal{D}} = \beta_1 + 1$, $\theta_{\mathcal{N}} = \beta_2 + 1$ and γ_i and γ_t are firm and time fixed effects, respectively. In line with our empirical results of Section 3, growth rates are measured over four quarters, meaning our estimated elasticities measure the degree of substitutability over a one-year horizon.

Constructing the covariates. To build the vectors *Diverse* and *Non-diverse*, we first construct firm-level input-output matrices ($\mathbf{\Omega}, \mathbf{\Omega}_{\mathcal{D}},$ and $\mathbf{\Omega}_{\mathcal{N}}$) for each quarter in the sample. Where pairwise transaction data exist in Compustat for any two given firms, we compute the corresponding input-output element as the value of sales from the supplying firm to the customer firm, as a fraction of the customer firm's total sales. In line with Baqaee and Farhi (2020), when there is no such data, we combine firms' sales data with industry-level input-output data from the BEA to proxy for expenditure shares at the firm level. With the firm-level input-output matrices in hand, we compute Leontief inverse matrices $\mathbf{\Psi} = (I - \mathbf{\Omega})^{-1}$. Next, the matrix diag($\boldsymbol{\lambda}$) is constructed using firms' pre-shock sales data in Compustat. Capital expenditure shares $\boldsymbol{\eta}$ are computed using data on firms' book value of physical capital and estimates of Compustat firms' intangible capital from Peters and Taylor (2017).[35] We deflate the resulting firm-level capital stocks using the GDP deflator. The user cost of capital is given by the sum of the risk-free real interest rate, depreciation rate, and risk premium.[36] Finally, we build the shock vector $\Delta \log \mathbf{z}$ from nominal disaster damages data from EM-DAT and county-level estimates of capital stocks. We compute the rate of capital destruction of a given county by dividing the total disaster damage of that county by the value of its capital stock. We assume all firms in the county are subject to the same shock. In Appendix B we provide a more detailed discussion on the construction of the firm-level input-output matrices, capital expenditure shares, and shock vectors.

Estimates of $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$. Table 6 reports the estimates for the elasticities of substitution $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ implied by regression (9) over three time horizons; one year, one quarter and two quarters. When "Disaster Quarters Only" is selected, the estimates correspond to a reduced sample of quarters in which at least one natural disaster occurred. Across all quarters, we find productive inputs to be gross substitutes for diverse firms over a one-year horizon ($\theta_{\mathcal{D}} = 2.106$, std. err. = 0.446). We also estimate an elasticity of substitution of $\theta_{\mathcal{N}} = 0.302$ (std. err. = 0.462) for non-diverse firms, suggesting inputs are

[35] See Appendix B for more detail on how we construct the capital expenditure shares using data from Peters and Taylor (2017).

[36] Following the methodology of De Loecker, Eeckhout and Unger (2020), we estimate the user cost of capital by setting the depreciation rate and risk premium jointly to 12%. As robustness, we also compute alternative estimates of the user cost, following the methodology of Baqaee and Farhi (2020), which adjusts for capital gains. All results are invariant to the alternative rental price of capital.

Table 6: Estimates of Elasticities of Substitution

	One Year (Baseline)		One Quarter		Two Quarters	
	(1)	(2)	(3)	(4)	(5)	(6)
$\theta_{\mathcal{D}}$	2.106^{**}	1.932^{**}	1.183	1.226	1.132	1.184
	[0.446]	[0.474]	[0.303]	[0.307]	[0.412]	[0.424]
$\theta_{\mathcal{N}}$	0.302	0.752	0.992	0.972	0.696	1.032
	[0.462]	[0.494]	[0.339]	[0.342]	[0.447]	[0.453]
Disaster Quarters Only		✓		✓		✓

Notes: This table reports estimates for regression specification (9). The dependent variable is the log change in firms' Domar weight over different time horizons. All regressions include firm and quarter fixed effects. Robust standard errors are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

complements for non-diverse firms. When we restrict the sample to quarters in which at least one natural disaster occurred, our estimates for the elasticities are $\theta_{\mathcal{D}} = 1.932$ and $\theta_{\mathcal{N}} = 0.752$. We take the estimates from column (2) of Table 6 as our preferred results. Over shorter horizons, we estimate elasticities slightly greater than one for diverse firms (between 1.132 and 1.226). For non-diverse firms, our estimates range from 0.696 to 1.032 over one- and two-quarters. However, over all time horizons, our estimate of $\theta_{\mathcal{N}}$ is not statistically different from one, so we cannot reject the hypothesis that production functions are Cobb-Douglas for non-diverse firms. Similarly, we cannot rule out Cobb-Douglas production for diverse firms over time horizons of less than one year. In summary, our one-year estimates provide strong evidence that inputs are substitutes for diverse firms and weak evidence that inputs are complements for non-diverse firms.

Our estimates are comparable to those of other studies in the literature. Oberfield and Raval (2021) estimate the elasticity of substitution between material and non-material inputs using plant-level manufacturing data from the U.S. Census of Manufacturing and Annual Survey of Manufactures, estimating an elasticity between 0.57 and 1.03, depending on the year.[37] Peter and Ruane (2020) use Indian plant-level manufacturing data to estimate an elasticity of 4.69 between eight broad categories of material inputs over a seven-year time horizon.[38] Over shorter time horizons (five years), Peter and

[37]Additionally, Oberfield and Raval (2021) estimate the elasticity of substitution between capital and labor at the plant level to be between 0.22 and 0.66, depending upon the census year and identification strategy used.

[38]Peter and Ruane (2020) also estimate elasticities of 0.43 between energy, materials, and

Ruane (2020) estimate an elasticity of substitution between material inputs of 1.5, which is roughly consistent with our baseline estimates. In an exercise similar to ours, Carvalho et al. (2021) use proprietary Japanese financial data to estimate a firm-level elasticity of substitution between primary inputs (capital and labor) and intermediates of 0.56. In line with our findings, Carvalho et al. (2021) also find evidence of substitutability between various intermediate inputs, estimating a firm-level elasticity of 1.18. These estimates are larger than those of Boehm, Flaaen and Pandalai-Nayar (2019b), who also use the 2011 Great East Japan Earthquake to estimate an elasticity of substitution between factors and materials of 0.03 and between domestic and foreign materials of 0.55.[39]

4.5 Estimating the macroeconomic benefit of supply base diversification

With estimates of the elasticities of substitution $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ in hand, we use the model to quantify the macroeconomic benefit of supply base diversification, defined as the change in real GDP due to substitution by diverse firms. We begin with the observation that, according to the model, the impact on the economy's aggregate output is given by

$$\Delta \log Y = \underbrace{\boldsymbol{\eta}' \Delta \log \mathbf{z}}_{\text{First-order}} + \underbrace{\frac{1}{2} \cdot \Delta \log \mathbf{z}' \cdot \operatorname{diag}(\boldsymbol{\eta}) \frac{d \log \boldsymbol{\eta}}{d \log \mathbf{z}} \Delta \log \mathbf{z}}_{\text{Second-order}}$$

up to a second-order of approximation in the size of the shock, where $\frac{d \log \boldsymbol{\eta}}{d \log \mathbf{z}}$ is an $N \times N$ matrix with ij^{th} element given by $\frac{d \log \eta_i}{d \log z_j}$. The second-order terms capture how firms' substitution patterns affect aggregate output since changes in capital expenditure shares are dependent on $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ (as per Proposition 2). The above expression, therefore, provides us with an avenue for estimating how substitution by diverse firms influences real GDP. To this end, we set $\theta_{\mathcal{N}} = 1$, meaning non-diverse firms do not change their demand expenditure in response to shocks.[40] A value of $\theta_{\mathcal{N}} = 1$ implies that all second-

services and 0.62 between primary factors (capital and labor) and intermediates.

[39]At the sector-level, Atalay (2017) finds evidence of gross complementarity between intermediate inputs, estimating an elasticity between 0 and 0.2. Notably, Peter and Ruane (2020) present evidence of lower elasticities between broad intermediate input categories at higher levels of aggregation.

[40]Indeed, from the results in Table 6 we cannot rule out Cobb-Douglas production technologies for non-diverse firms.

order effects are solely attributable to the behavior of diverse firms.[41] Defining $\mathcal{L} \equiv \frac{1}{2} \cdot \Delta \log \mathbf{z}' \cdot \text{diag}(\boldsymbol{\eta}) \frac{d \log \boldsymbol{\eta}^*}{d \log \mathbf{z}} \Delta \log \mathbf{z}$, where $\frac{d \log \boldsymbol{\eta}^*}{d \log \mathbf{z}}$ is evaluated at the point $\theta_{\mathcal{N}} = 1$, the following proposition provides an expression that quantifies the benefit of supply base diversification in terms of real output.

Proposition 3. *The macroeconomic benefit of supply base diversification is given by*

$$\mathcal{L} = (\theta_{\mathcal{D}} - 1) \cdot \frac{1}{2} \cdot \Delta \log \mathbf{z}' \cdot \text{diag}(\boldsymbol{\eta}) \Delta_{\mathcal{D}} \cdot \Delta \log \mathbf{z} \tag{10}$$

where the ij^{th} element of the $N \times N$ matrix $\Delta_{\mathcal{D}}$ is given by

$$\Delta_{\mathcal{D}}^{ij} = \begin{cases} f_1\left(\boldsymbol{\Omega}_{\mathcal{D}}, \boldsymbol{\lambda}_{\mathcal{D}}, \eta_j\right), & \text{if } i \in \mathcal{D} \\ f_2\left(\boldsymbol{\Omega}_{\mathcal{D}}, \boldsymbol{\lambda}_{\mathcal{D}}, \eta_j\right), & \text{if } i \in \mathcal{N} \end{cases}$$

Proof. See Appendix A.

Equation (10) provides an expression that isolates the contribution of substitution by diverse firms on real GDP growth. Formally, the equation evaluates the *second-order* change in output at the point $\theta_{\mathcal{N}} = 1$.[42] The benefit of diversity at the macroeconomic level (measured by $\mathcal{L}$) is increasing in $\theta_{\mathcal{D}}$ (the elasticity of substitution of diverse firms) and producers' capital expenditure shares. Notably, the elements of the matrix $\Delta_{\mathcal{D}}$ are a function of input-output parameters and take one of two functional forms depending upon whether the customer firm i is diverse or non-diverse. In the Proof of proposition 3, we explicitly characterize $f_1\left(\boldsymbol{\Omega}_{\mathcal{D}}, \boldsymbol{\lambda}_{\mathcal{D}}, \eta_j\right)$ and $f_2\left(\boldsymbol{\Omega}_{\mathcal{D}}, \boldsymbol{\lambda}_{\mathcal{D}}, \eta_j\right)$. Crucially, the matrix $\Delta_{\mathcal{D}}$ depends upon the relative exposure of diverse firms to the shocks (Proposition 2) and hence on the specific structure of the economy's production network. Our quantitative results below reveal that diverse firms lessened the negative impact on real GDP following the largest natural disasters in the US over the last three decades. Our empirical findings and quantitative exercise suggest that mitigating supply chain risk can deliver both micro- and macroeconomic benefits.

Results. We estimate the effect of supply base diversity on real GDP by first selecting quarters in which total disaster damages exceeded \$50 bil-

[41] See Baqaee and Farhi (2019) for an elaboration of this point.

[42] More specifically, $\mathcal{L} = \frac{1}{2} \cdot \Delta \log \mathbf{z}' \cdot \text{diag}(\boldsymbol{\eta}) \left.\frac{d \log \boldsymbol{\eta}}{d \log \mathbf{z}}\right|_{\theta_{\mathcal{N}}=1} \Delta \log \mathbf{z}$.

Table 7: Disaster Quarters Used for Counterfactual Analysis

Date	Disasters	Total Damage ($bn)
1992 Q3	Hurricane Andrew, Iniki	57.4
1994 Q1	Northridge Earthquake	51.7
2004 Q3	Hurricane Ivan, Jeanne, Frances, Charley	71.8
2005 Q3	Hurricane Katrina, Rita	184.5
2012 Q4	Hurricane Sandy	55.7
2017 Q3	Hurricane Harvey, Irma	158.6

Notes: This table reports the disaster quarters used to calculate the macroeconomic benefit of diversity in Figure 10. Total damages are calculated as the sum of damages caused by all natural disasters in a given quarter. Estimates of disaster damages are from EM-DAT's public database and FEMA's *OpenFEMA Disaster Declarations* dataset, deflated to 2017 USD.

lion across all US states.[43] Our sample has six such quarters, dating from 1992Q3 to 2017Q3. Table 7 reports the natural disasters and corresponding damages during each quarter. As shown in the table, hurricanes account for the majority of total damages, the largest of which being Katrina, with damages exceeding $160 billion. The Northridge earthquake of '94 is the only non-hurricane disaster with damages in excess of $50 billion.

To estimate the benefit of diversity at the macroeconomic level, we first compute the change in real GDP due to the behavior of diverse firms via equation (10) using only the shocks listed in Table 7. Then, for each quarter, we calculate the *percentage gain* in real GDP growth attributed to diverse firms as

$$\frac{\mathcal{L}_q}{|\boldsymbol{\eta}_q' \cdot \Delta \log \mathbf{z}_q|},$$

where $\mathcal{L}_q$ is the benefit expressed as the percentage change in GDP growth, $|\boldsymbol{\eta}_q' \cdot \Delta \log \mathbf{z}_q|$ is the absolute value of the first-order change in real GDP, and q indexes each quarter listed in Table 7. The denominator of the above expression can be interpreted as the change in aggregate output in the absence of diverse firms. We take the absolute value of the first-order effect because it is always negative, whereas $\mathcal{L}_q$ is always positive. The resulting fraction, therefore, measures the percentage gain in GDP growth relative to the counterfactual scenario in which diverse firms do not substitute across inputs ($\theta_{\mathcal{D}} = 1$). For example, in 2004Q3, we calculate a percentage gain in GDP growth of 11.6%. According to the BEA, the observed year-on-year GDP growth rate was 3.49%. Therefore, our estimate implies that GDP growth would have only been 3.09% in the absence of diverse firms.

[43]We focus on the quarters in which disaster damages were most significant for computational reasons.

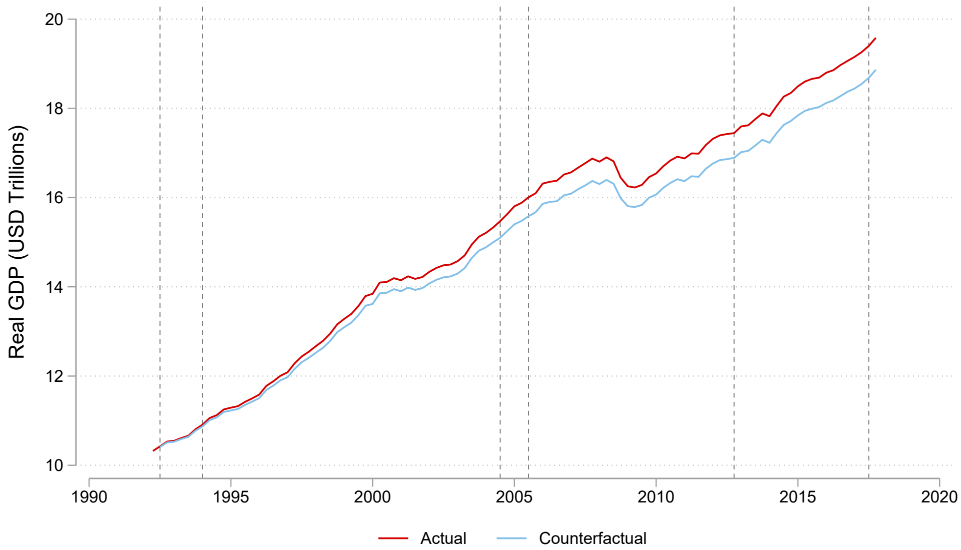

Figure 10: Macroeconomic Benefit of Supply Base Diversification

Note: The red line plots US quarterly real GDP from 1992Q2 to 2017Q4 (2017 USD, trillions). The blue line represents the counterfactual evolution of real GDP in the absence of diverse firms. The area between the two series captures the aggregate benefit of supply base diversification between 1992 and 2017. Vertical dashed lines depict the disaster quarters used to compute the counterfactual real GDP series.

Next, we calculate the mean gain across the six quarters as $\frac{1}{6}\sum_{q=1}^{6}\frac{\mathcal{L}_q}{|\boldsymbol{\eta}_q'\cdot\Delta\log\mathbf{z}_q|}$ to get an average gain of 5.83%. Then, for all quarters between 1992Q2 and 2017Q4, we compute the counterfactual GDP growth rate by reducing the observed growth rate by 5.83%. Finally, we use the adjusted growth rates to generate a counterfactual real GDP series that omits the behavior of diverse firms. The resulting series is shown in Figure 10 (blue line), where it is plotted against observed US quarterly real GDP (in trillions of 2017 USD). As the figure shows, by the end of 2017, quarterly real GDP would have been $\approx$ \$740 billion lower than observed. The area between the two series shown in Figure 10 captures the total gain in aggregate output between 1992 and 2017, which amounts to \$37.6 trillion.

Our estimate of supply base diversity's overall economy-wide effect underscores the idea that large welfare gains can be made by reducing an economy's supply chain risk. How policymakers can best incentivize firms to invest in supply-chain risk management is an important question for future research. Policies that reduce risk by increasing domestic supply chain diversity may prevent economic shocks from having sizable aggregate effects.

5 Conclusion

We explore the effects of supply base diversity on the propagation of shocks through firm-level input-output linkages. Leveraging the exogenous and localized nature of natural disasters in the US between 1978 and 2017, we find strong evidence that firms with supply bases spread across many i) suppliers, ii) geographies, or iii) industries experience reductions in sales growth $\approx 60-70\%$ smaller than non-diversified firms when at least one supplier is struck with a natural disaster. Using a general equilibrium model of production networks, we estimate the overall macroeconomic benefit of diversification. The ability of diverse firms to substitute across inputs translates into an $\approx$ \$740 billion gain in quarterly real GDP in 2017.

At the microeconomic level, our results suggest that firms benefit from diversification. Diversified firms can find suitable alternatives when a supplier experiences an output disruption, limiting the transmission effect of the shock. However, increasing supply base diversity is not an obvious decision for firms. Firms face a trade-off between the benefits of supplier consolidation and economies of scale versus the risk mitigation associated with supplier diversification. To an individual firm, the optimal level of diversification depends on many factors and is beyond the scope of this paper. Additionally, we document the effects of diversity on publicly-listed firms in the US. In the absence of complete firm-to-firm transaction data among all US firms, we cannot test how our results generalize to the broader economy, though we consider this important in future work.

At the macroeconomic level, the extent of supply base diversity has significant implications for aggregate fluctuations. In particular, our results show that substitution across inputs by diverse firms attenuates the impact of adverse supply shocks on real GDP. In quantifying the benefits of diversification, this study provides the impetus for policymakers to better scrutinize the composition of the US production network and incentivize firms to increase their level of supply base diversity.

Appendix

Appendix A. Proofs

Proof of Proposition 1. First multiply both sides of equation (6) by $\frac{p_i}{\text{GDP}}$ to get $\lambda_i = b_i + \sum_{j\in\mathcal{D}}\Omega_{ji}\lambda_j + \sum_{j\in\mathcal{N}}\Omega_{ji}\lambda_j$, where $b_i \equiv \frac{p_i c_i}{\text{GDP}}$. Total differentiation of the above equation implies

$$d\lambda_i = db_i + \sum_{j\in\mathcal{D}}\Omega_{ji}d\lambda_j + \sum_{j\in\mathcal{D}}\lambda_j d\Omega_{ji} + \sum_{j\in\mathcal{N}}\Omega_{ji}d\lambda_j + \sum_{j\in\mathcal{N}}\lambda_j d\Omega_{ji}.$$

Solving for changes in Domar weights and writing the resulting equation in matrix form, we get

$$d\boldsymbol{\lambda}' = d\mathbf{b}'\boldsymbol{\Psi} + \boldsymbol{\lambda}'_{\mathcal{D}}d\boldsymbol{\Omega}_{\mathcal{D}}\boldsymbol{\Psi} + \boldsymbol{\lambda}'_{\mathcal{N}}d\boldsymbol{\Omega}_{\mathcal{N}}\boldsymbol{\Psi}$$

The i^{th} element of the above equation is then given by

$$d\lambda_i = \sum_{k\in S} db_k\Psi_{ki} + \sum_{m\in S}\sum_{k\in\mathcal{D}}\lambda_k d\Omega_{km}\Psi_{mi} + \sum_{m\in S}\sum_{k\in\mathcal{N}}\lambda_k d\Omega_{km}\Psi_{mi},$$

from which we can write

$$d\log\lambda_i = \lambda_i^{-1}\sum_{m\in S}\sum_{k\in\mathcal{D}}\Omega_{km}\lambda_k\Psi_{mi}d\log\Omega_{km} + \lambda_i^{-1}\sum_{m\in S}\sum_{k\in\mathcal{N}}\lambda_k\Omega_{km}\Psi_{mi}d\log\Omega_{km}. \tag{11}$$

Note that the specification of Cobb-Douglas preferences implies $d\log b_i = 0$ for all $i\in\mathcal{S}$. Next, the first-order condition with respect to intermediate input x_{km} purchased by firm k implies

$$\Omega_{km} = \frac{p_m x_{km}}{p_k y_k} = p_k^{\theta_s-1}\omega_{km}p_m^{1-\theta_s} \tag{12}$$

where $\theta_s = \theta_{\mathcal{D}}$ if firm k is diverse, or $\theta_s = \theta_{\mathcal{N}}$ if k is non-diverse. Similarly, the first-order condition with respect to capital yields

$$\frac{\eta_k}{\lambda_k} = \frac{rk_k}{p_k y_k} = p_k^{\theta_s-1}\mu_k z_k^{\theta_s-1}r^{1-\theta_s}$$

Consequently, by equation (12)

$$d\log\Omega_{km} = (\theta_s - 1)\left[d\log p_k - d\log p_m\right],$$

and plugging the above equation into (11) implies

$$d\log\lambda_i = (\theta_{\mathcal{D}}-1)\lambda_i^{-1}\sum_{m\in S}\sum_{k\in\mathcal{D}}\Omega_{km}\lambda_k\Psi_{mi}\left[d\log p_k - d\log p_m\right]$$
$$+(\theta_{\mathcal{N}}-1)\lambda_i^{-1}\sum_{m\in S}\sum_{k\in\mathcal{N}}\lambda_k\Omega_{km}\Psi_{mi}\left[d\log p_k - d\log p_m\right]$$

Writing the above equation in matrix form, noting that $d\log\mathbf{p}$ is the $N\times 1$ vector of log price changes, we get

$$d\log\boldsymbol{\lambda} = (\theta_{\mathcal{D}}-1)\mathrm{diag}\left(\boldsymbol{\lambda}\right)^{-1}\boldsymbol{\Psi}'\left(\boldsymbol{\Omega}'_{\mathcal{D}}\mathrm{diag}\left(d\log\mathbf{p}\right)-\mathrm{diag}\left(d\log\mathbf{p}\right)\boldsymbol{\Omega}'_{\mathcal{D}}\right)\boldsymbol{\lambda}_{\mathcal{D}}$$
$$+(\theta_{\mathcal{N}}-1)\mathrm{diag}\left(\boldsymbol{\lambda}\right)^{-1}\boldsymbol{\Psi}'\left(\boldsymbol{\Omega}'_{\mathcal{N}}\mathrm{diag}\left(d\log\mathbf{p}\right)-\mathrm{diag}\left(d\log\mathbf{p}\right)\boldsymbol{\Omega}'_{\mathcal{N}}\right)\boldsymbol{\lambda}_{\mathcal{N}} \quad (13)$$

where diag($\mathbf{X}$) denotes a diagonal matrix with diagonal entries given by vector $\mathbf{X}$. Equation (13) characterizes changes in Domar weights in terms of changes in prices, the economy's production network, and the elasticities of substitution $(\theta_{\mathcal{D}},\theta_{\mathcal{N}})$.

Next, we characterize $d\log\mathbf{p}$ in terms of the vector of capital-augmenting shocks $d\log\mathbf{z}$. Firstly, note that firm i's unit cost function is given by

$$p_i = \left(z_i^{\theta_s-1}\mu_i r^{1-\theta_s}+\sum_{j\in\mathcal{S}}\omega_{ij}p_j^{1-\theta_s}\right)^{\frac{1}{1-\theta_s}}.$$

Total (log) differentiation of the above equation yields

$$d\log p_i = p_i^{\theta_s-1}z_i^{\theta_s-1}\mu_i r^{1-\theta_s}d\log r - p_i^{\theta_s-1}z_i^{\theta_s-1}\mu_i r^{1-\theta_s}d\log z_i + \sum_{j\in\mathcal{S}}p_i^{\theta_s-1}\omega_{ij}p_j^{1-\theta_s}d\log p_j.$$

Since the rental price of capital is the numeraire, and given the expressions for Ω_{ij} and $\frac{\eta_i}{\lambda_i}$ derived earlier, the above equation can be written as

$$d\log p_i = \sum_{j\in\mathcal{S}}\Omega_{ij}d\log p_j - \frac{\eta_i}{\lambda_i}d\log z_i.$$

Rearranging and solving for $d\log p_i$, gives

$$d\log p_i = -\sum_{h\in\mathcal{S}}\Psi_{ih}\frac{\eta_h}{\lambda_h}d\log z_h \quad (14)$$

Writing the above equation in matrix form, $d\log\mathbf{p} = -\mathrm{diag}\left(d\log\mathbf{z}\right)\boldsymbol{\Psi}\cdot\mathrm{diag}(\boldsymbol{\lambda})^{-1}\boldsymbol{\eta}$, and substituting into equation (13), yields

$$
\begin{aligned}
d\log \boldsymbol{\lambda} = {} & (\theta_{\mathcal{D}}-1)\mathrm{diag}(\boldsymbol{\lambda})^{-1}\boldsymbol{\Psi}'\left(d\log \mathbf{z}\circ \mathbf{M}\cdot \boldsymbol{\Omega}'_{\mathcal{D}} - \boldsymbol{\Omega}'_{\mathcal{D}}\cdot d\log \mathbf{z}\circ \mathbf{M}\right)\boldsymbol{\lambda}_{\mathcal{D}} \\
& + (\theta_{\mathcal{N}}-1)\mathrm{diag}(\boldsymbol{\lambda})^{-1}\boldsymbol{\Psi}'\left(d\log \mathbf{z}\circ \mathbf{M}\cdot \boldsymbol{\Omega}'_{\mathcal{N}} - \boldsymbol{\Omega}'_{\mathcal{N}}\cdot d\log \mathbf{z}\circ \mathbf{M}\right)\boldsymbol{\lambda}_{\mathcal{N}}.
\end{aligned}
$$

where $\mathbf{M} \equiv \mathrm{diag}\left(\boldsymbol{\Psi}\cdot \mathrm{diag}(\boldsymbol{\lambda})^{-1}\boldsymbol{\eta}\right)$. By taking the derivative of $d\log \boldsymbol{\lambda}$ with respect to $d\log z_j$, the above equation coincides with equation (7):

$$
\begin{aligned}
\frac{d\log \lambda_i}{d\log z_j} = {} & (\theta_{\mathcal{D}}-1)\frac{\eta_j}{\lambda_i\lambda_j}\sum_{k\in\mathcal{D}}\sum_{m\in\mathcal{S}}\Omega_{km}\lambda_k\Psi_{mi}\left(\Psi_{mj}-\Psi_{kj}\right) \\
& + (\theta_{\mathcal{N}}-1)\frac{\eta_j}{\lambda_i\lambda_j}\sum_{k\in\mathcal{N}}\sum_{m\in\mathcal{S}}\Omega_{km}\lambda_k\Psi_{mi}\left(\Psi_{mj}-\Psi_{kj}\right).
\end{aligned}
$$

■

Proof of Proposition 2. From the households' optimization, the first-order condition with respect to c_i implies

$$c_i = a_i p_i^{-1}(rK).$$

Therefore, $d\log c_i = -d\log p_i$ since r is the numeraire and the aggregate stock of capital is assumed to be in fixed supply. From the Divisia index for changes in real output, $d\log Y = \sum_{k\in\mathcal{S}} b_k d\log c_k$, we get

$$\frac{d\log Y}{d\log z_i} = -\sum_{k\in\mathcal{S}} b_k \frac{d\log p_k}{d\log z_i}$$

From equation (14), we can write

$$\frac{d\log Y}{d\log z_i} = \sum_{k\in\mathcal{S}} b_k \Psi_{ki}\frac{\eta_i}{\lambda_i}.$$

Noting that $\sum_{k\in\mathcal{S}} b_k\Psi_{ki} = \lambda_i$, the above equation can be written as

$$\frac{d\log Y}{d\log z_i} = \eta_i.$$

The second-order impact of a common capital-augmenting shock hitting firm i and j is equal to the change in i's capital share in response to the shock to j:

$$\frac{d^2 \log Y}{d\log z_j d\log z_i} = \frac{d\eta_i}{d\log z_j} = \eta_i \frac{d\log \eta_i}{d\log z_j}.$$

The first-order condition with respect to capital implies

$$\eta_i = p_i^{\theta_s - 1} \mu_i \lambda_i z_i^{\theta_s - 1} r^{1-\theta_s},$$

therefore,

$$\frac{d\log \eta_i}{d\log z_j} = (\theta_s - 1)\frac{d\log p_i}{d\log z_j} + (\theta_s - 1)\frac{d\log z_i}{d\log z_j} + \frac{d\log \lambda_i}{d\log z_j} + (1-\theta_s)\frac{d\log r}{d\log z_j}.$$

We can write the above equation as

$$\frac{d\log \eta_i}{d\log z_j} = (1-\theta_s)\left[\sum_{h\in\mathcal{S}} \Psi_{ih}\frac{\eta_h}{\lambda_h}\frac{d\log z_h}{d\log z_j} - \frac{d\log z_i}{d\log z_j}\right] + \frac{d\log \lambda_i}{d\log z_j}.$$

Finally,

$$\frac{d^2 \log Y}{d\log z_j d\log z_i} = (1-\theta_s)\left[\eta_i \Psi_{ij}\frac{\eta_j}{\lambda_j} - \mathbf{1}(i=j)\right] + \eta_i \frac{d\log \lambda_i}{d\log z_j}.$$

■

Proof of Proposition 3. Let $\Delta \log Y^*$ denote the change in real GDP to a second-order under the counterfactual where $\theta_{\mathcal{N}} = 1$. More specifically,

$$\Delta \log Y^* = \boldsymbol{\eta}' \Delta \log \mathbf{z} + \frac{1}{2} \cdot \Delta \log \mathbf{z}' \mathrm{diag}(\boldsymbol{\eta}) \frac{d\log \boldsymbol{\eta}^*}{d\log \mathbf{z}} \Delta \log \mathbf{z}$$

where $\frac{d\log \boldsymbol{\eta}^*}{d\log \mathbf{z}}$ is the matrix $\frac{d\log \boldsymbol{\eta}}{d\log \mathbf{z}}$ evaluated at $\theta_{\mathcal{N}} = 1$. To see how we get to the above equation, first note that the change in real GDP in response to a vector of shocks $\Delta \log \mathbf{z}$, up to a second-order of approximation is given by

$$\Delta \log Y = \sum_{i\in\mathcal{S}} \frac{d\log Y}{d\log z_i}(\Delta \log z_i) + \frac{1}{2} \cdot \sum_{i\in\mathcal{S}} \sum_{j\in\mathcal{S}} \frac{d^2 \log Y}{d\log z_i d\log z_j}(\Delta \log z_i)(\Delta \log z_j)$$

which, using Proposition 2, can be written as

$$\Delta \log Y = \sum_{i\in\mathcal{S}} \eta_i (\Delta \log z_i) + \frac{1}{2} \cdot \sum_{i\in\mathcal{S}} \sum_{j\in\mathcal{S}} \eta_i \frac{d\log \eta_i}{d\log z_j}(\Delta \log z_i)(\Delta \log z_j).$$

Written in matrix form, the above equation becomes, $\Delta \log Y = \boldsymbol{\eta}' \Delta \log \mathbf{z} + \frac{1}{2} \cdot \Delta \log \mathbf{z}' \mathrm{diag}(\boldsymbol{\eta}) \frac{d \log \boldsymbol{\eta}}{d \log \mathbf{z}} \Delta \log \mathbf{z}$.

Recall from the proof of Proposition 2 that changes in capital expenditure shares are given by

$$\frac{d \log \eta_i}{d \log z_j} = (1 - \theta_s) \left[\Psi_{ij} \frac{\eta_j}{\lambda_j} - \mathbf{1}(i = j) \right] + \frac{d \log \lambda_i}{d \log z_j}.$$

where θ_s corresponds to the elasticity of substitution of firm i. Our objective is to evaluate all changes in capital expenditure shares $\frac{d \log \eta_i}{d \log z_j}$ at $\theta_{\mathcal{N}} = 1$. Notably, these expressions depend upon whether firm i is diverse or non-diverse. For example, if $i \in \mathcal{N}$, then

$$\frac{d \log \eta_i^*}{d \log z_j} = \frac{d \log \lambda_i}{d \log z_j} = (\theta_{\mathcal{D}} - 1) \frac{\eta_j}{\lambda_i \lambda_j} \sum_{m \in S} \sum_{k \in \mathcal{D}} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right),$$

which is a consequence of equation (7). By contrast, if $i \in \mathcal{D}$, then

$$\begin{aligned} \frac{d \log \eta_i^*}{d \log z_j} &= (1 - \theta_{\mathcal{D}}) \left[\Psi_{ij} \frac{\eta_j}{\lambda_j} - \mathbf{1}(i = j) \right] + \frac{d \log \lambda_i}{d \log z_j} \\ &= (1 - \theta_{\mathcal{D}}) \left[\Psi_{ij} \frac{\eta_j}{\lambda_j} - \mathbf{1}(i = j) \right] + (\theta_{\mathcal{D}} - 1) \frac{\eta_j}{\lambda_i \lambda_j} \sum_{m \in S} \sum_{k \in \mathcal{D}} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right) \\ &= (\theta_{\mathcal{D}} - 1) \left[-\Psi_{ij} \frac{\eta_j}{\lambda_j} + \mathbf{1}(i = j) + \frac{\eta_j}{\lambda_i \lambda_j} \sum_{m \in S} \sum_{k \in \mathcal{D}} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right) \right] \end{aligned}$$

Defining an $N \times N$ matrix $\Delta_{\mathcal{D}}$, where the ij^{th} element is given by

$$\Delta_{\mathcal{D}}^{ij} = \begin{cases} -\Psi_{ij} \frac{\eta_j}{\lambda_i \lambda_j} + \mathbf{1}(i = j) + \frac{\eta_j}{\lambda_i \lambda_j} \sum_{m \in S} \sum_{k \in \mathcal{D}} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right), & \text{if } i \in \mathcal{D} \\ \frac{\eta_j}{\lambda_i \lambda_j} \sum_{m \in S} \sum_{k \in \mathcal{D}} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right), & \text{otherwise} \end{cases}$$

Therefore,

$$\mathcal{L} = (\theta_{\mathcal{D}} - 1) \frac{1}{2} \cdot \sum_{i \in \mathcal{S}} \sum_{j \in \mathcal{S}} \eta_i \Delta_{\mathcal{D}}^{ij} (\Delta \log z_i)(\Delta \log z_j)$$

or, in matrix form,

$$\mathcal{L} = (\theta_{\mathcal{D}} - 1) \cdot \frac{1}{2} \cdot \Delta \log \mathbf{z}' \cdot \mathrm{diag}(\boldsymbol{\eta}) \Delta_{\mathcal{D}} \cdot \Delta \log \mathbf{z}$$

which is equation (10).

■

Appendix B. Data for Quantitative Application

Input-Output Data and Aggregate Data. Our input-output data comes from the BEA's annual "Use" tables from 1978-2017 before redefinitions.[44] In line with Baqaee and Farhi (2020), we do not make a distinction between industries and commodities and assume each industry produces one commodity. We drop all government sectors from each table, as well as scrap, used and secondhand goods, and noncomparable imports, leaving us with 61 industries for the years 1978-1996 and 66 sectors for the years 1997-2017.

The time series of aggregate capital, intermediate input, and value-added shares in gross output comes from the BEA's Integrated Industry-Level Production Account (KLEMS). We use the KLEMS data to construct capital stock measures at the 5-digit FIPS level and firm-level measures of capital expenditure shares (η_i) and Domar weights (λ_i) in conjunction with the quarterly Compustat data.

Natural Disaster Data and County-Level Data. The shock vector ($\Delta \log \mathbf{z}$) is constructed using data on nominal damages from EM-DAT and county-level estimates of economic activity from the BEA. We first generate estimates of county-level capital stocks by multiplying the nominal income of a given five-digit FIPS code by the aggregate capital share (using the KLEMS data).[45] We compute the county-level shock as nominal FIPS-level damages as a fraction of the county's capital stock. FIPS-level damages are measured as the total value of damages caused by *all* natural disasters hitting a particular five-digit FIPS code in a given quarter. More specifically, we first compute the FIPS-level damage for a *given* natural disaster as the total damage caused by that disaster divided by the number of counties affected. Then, to estimate the damage for a given FIPS-quarter, we aggregate across all disasters hitting the county in the quarter. We assume all firms in a given county are subject to the same shock.

[44] "Before redefinitions" refers to the treatment of secondary production of industries. If a given industry produces a secondary product that is assumed to have very different inputs than the other products of the producing industry, the secondary product (output and inputs) is moved (redefined) to the industry to which the product is primary. The input-output tables we use do not correct for this.

[45] We use the BEA's estimates of nominal income at the county level as these cover the years 1969-2020. Estimates of GDP at the county level are only available for 2001-2020.

Firm-Level Input-Output Data. The firm-level input-output tables are constructed using firm-level sales data and inter-firm transactions data from Compustat and the BEA sector-level input-output tables. Where bilateral transactions data exist for firm-quarter pairs (i.e., where the *salecs* variable is populated in Compustat), we compute the corresponding input-output element as the value of sales from the supplying firm to the customer firm, as a fraction of the customer's sales. When there is no such data, we impute the input-output data in a similar way to Baqaee and Farhi (2020). We first assign each firm to a sector in the BEA input-output tables using the concordance files provided by the BEA. Firms are mapped by NAICS codes at either the three- or four-digit level, depending on the level of disaggregation of a given industry in the BEA input-output tables). When NAICS codes are missing and SIC codes are populated, we assign firms to the most common NAICS code of firms that share the same SIC. Then, we compute,

$$\Omega_{ij} = \frac{\lambda_j}{\lambda_J}\Omega_{IJ} \quad i \in I, \quad j \in J$$

where λ_J is the Domar weight of the sector of the supplying firm, λ_j is the Domar weight of the supplying firm, and Ω_{IJ} is the sector-level input-output coefficient, which measures the expenditure by sector I on sector J's output as a fraction of I's revenues. Note also that firm i is in sector I, and firm j belongs to sector J. The sector-level input-output coefficients are calibrated to the BEA input-output table of the corresponding year.[46]

Firm-Level Domar Weights and Capital Expenditure Shares. Firm-level Domar weights are computed using quarterly sales data from Compustat. When sales data is negative, we set it to zero. To construct firm-level capital expenditure shares, we use firms' book value of property, plant, and equipment less accumulated depreciation (*ppentq* in Compustat) plus estimates of intangible capital from Peters and Taylor (2017) (variable *k_int* in WRDS Peters and Taylor dataset). Notably, *k_int* measures externally purchased intangible capital (Compustat item *intan*) plus internally created intangible capital (see Peters and Taylor (2017) for more details on the construction of this variable). Since estimates of intangible capital appear at the annual frequency, we linearly interpolate these data to generate quarterly

[46] We construct firm-level input-output tables for each quarter and assume sector-level input-output coefficients are constant across all four quarters of a given year.

estimates of firms' replacement costs of intangible capital.

With estimates of firm-quarter capital stocks in hand, we measure the value of capital services in a given quarter t as $r_t * k_{it}$, where r_t is the user-cost of capital in period t, and k_{it} is the sum of the book value of property, plant, and equipment and intangible capital. We use two measures of the user cost of capital. First, in line with De Loecker, Eeckhout and Unger (2020), we compute

$$r_t = (i_t - \pi_t) + RP + \delta$$

where i_t is the nominal interest rate, π_t is the CPI inflation rate, RP is a risk premium, and δ is a depreciation rate. As in De Loecker, Eeckhout and Unger (2020), we set the risk premium and depreciation rate exogenously at 12%. The interest rate i_t corresponds to the yield on 10-year Treasury bonds. The second measure of the rental price is given by

$$r_t = (i_t - \pi_t) + ERP_t - (1 - \delta_t) * \mathbb{E}[\Pi_{t+1}]$$

where $(i_t - \pi_t)$ is the risk-free real rate, ERP_t is the equity risk premium, which we take from Aswath Damodaran's website.[47] The rate of depreciation is computed as the current cost depreciation of fixed assets (series *M1TTOTL1ES000* from FRED) divided by the current cost gross stock of fixed assets (FRED series *K1TTOTL1ES000*, adjusted for depreciation). Finally, $\mathbb{E}[\Pi_{t+1}]$ is the expected capital gain, measured as the growth rate of the relative price of capital. More specifically, the capital gain is the growth rate in the investment price index divided by the PCE deflator (FRED series *PIRIC*).

[47]The equity risk premium data can be found at https://pages.stern.nyu.edu/~adamodar/.

Appendix C. Supplementary Figures and Tables

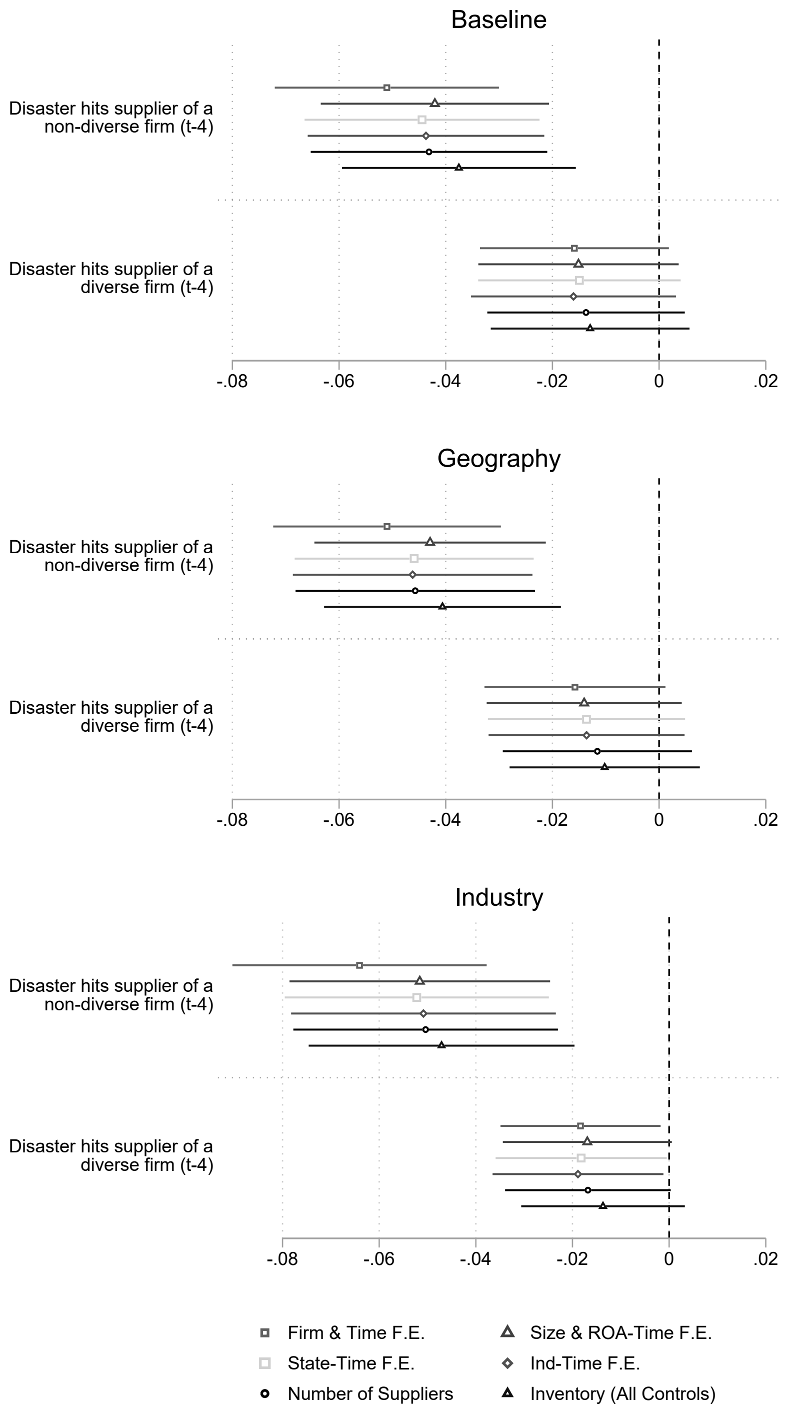

Figure C1: Downstream Propagation - Customer Diversity (Robustness)

Note: This figure shows results for different versions of specification (3), with the progressive inclusion of firm, time, size, return on assets (ROA) by quarter, state-time, and industry by quarter fixed effects.

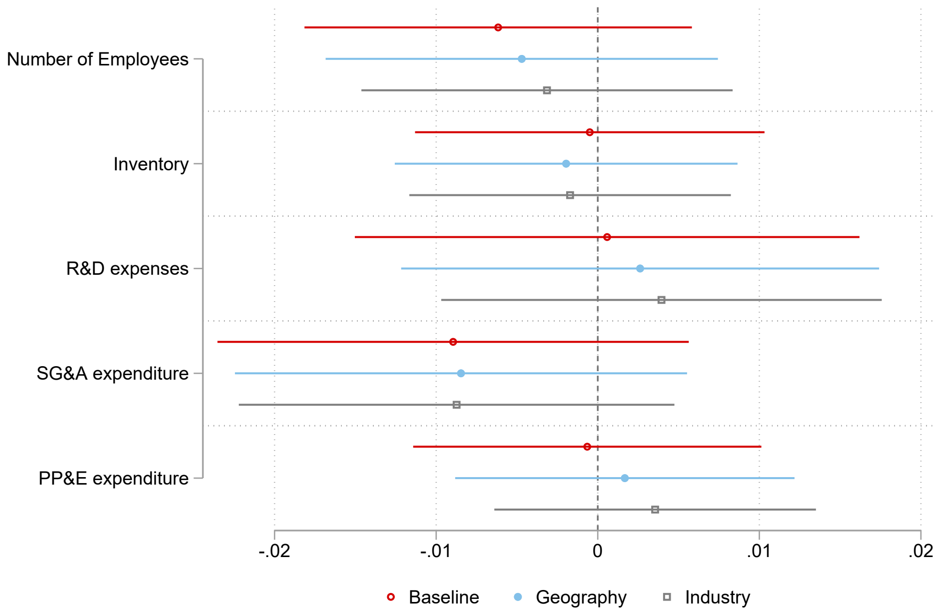

Figure C2: Orthogonality of Diversity Measures with Other Firm Attributes

Note: This figure shows the orthogonality of various firm attributes with each diversity indicator. *Number of employees* is firms' total employment (in tens of thousands). *Inventory*, *R&D expenses*, *SG&A expenditure* and *PP&E expenditure* are tercile dummies of (respectively) firms' value of inventories, R&D expenditure, Selling, General and Administrative expenditure and Property, Plant and Equipment spending as a proportion of total sales.

Table C1: Orthogonality of Supply Base Diversity and Input Specificity (Rauch)

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.031**	0.028**	0.032**	0.028**	0.041***	0.032**
	[0.013]	[0.013]	[0.012]	[0.013]	[0.015]	[0.015]
Disaster hits specific supplier $(t-4)$	-0.036***	-0.035***	-0.036***	-0.035***	-0.036***	-0.034***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Disaster hits one supplier $(t-4)$	-0.031***	-0.026**	-0.032***	-0.027**	-0.043***	-0.034**
	[0.011]	[0.011]	[0.011]	[0.011]	[0.013]	[0.013]
Disaster hits firm $(t-4)$	-0.023**	-0.024**	-0.023**	-0.024**	-0.023**	-0.024**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.012	-0.002	-0.014*	-0.005	-0.004	0.002
	[0.008]	[0.008]	[0.008]	[0.008]	[0.006]	[0.006]
Specific supplier (Rauch)	-0.007	-0.002	-0.007	-0.002	-0.007	-0.003
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	73,377	73,377	73,377	73,377	73,377	73,377
Adjusted R^2	0.212	0.232	0.212	0.232	0.212	0.232

Notes: This table presents estimates for specification (3), but with the inclusion of a dummy that indicates whether the firm has a specific supplier (using the classification of goods as differentiated or homogeneous from Rauch, 1999) and an interaction between this *specificity* dummy and *disaster hits supplier*. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and a control variable for the number of suppliers a customer firm has. Columns (2), (4), and (6) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter. Standard errors, represented in square brackets, are clustered at the firm level.* p<0.1; ** p<0.05; *** p<0.01.

Table C2: Orthogonality of Supply Base Diversity and Input Specificity (R&D)

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.031**	0.028**	0.032***	0.029**	0.040***	0.031**
	[0.013]	[0.013]	[0.012]	[0.013]	[0.015]	[0.015]
Disaster hits specific supplier $(t-4)$	-0.028*	-0.028*	-0.028*	-0.028*	-0.026*	-0.026*
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
Disaster hits one supplier $(t-4)$	-0.037***	-0.031***	-0.037***	-0.032***	-0.048***	-0.038***
	[0.010]	[0.011]	[0.010]	[0.011]	[0.012]	[0.013]
Disaster hits firm $(t-4)$	-0.023**	-0.024**	-0.023**	-0.024**	-0.022**	-0.023**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.012	-0.002	-0.014*	-0.005	-0.004	0.002
	[0.008]	[0.008]	[0.008]	[0.008]	[0.006]	[0.006]
Specific supplier (RD)	-0.013*	-0.005	-0.012*	-0.005	-0.012*	-0.005
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	73,377	73,377	73,377	73,377	73,377	73,377
Adjusted R^2	0.212	0.232	0.213	0.232	0.212	0.232

Notes: This table presents estimates for specification (3), but with the inclusion of a dummy that indicates whether the firm has a specific supplier (as measured by expenditure on research and development) and an interaction between this *specificity* dummy and *disaster hits supplier*. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and a control variable for the number of suppliers a customer firm has. Columns (2), (4), and (6) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter. Standard errors, represented in square brackets, are clustered at the firm level.* p<0.1; ** p<0.05; *** p<0.01.

Table C3: Downstream Propagation - Customer Diversity with Continuous Herfindahls

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.060***	0.050***	0.072***	0.063***	0.056**	0.046*
	[0.019]	[0.019]	[0.021]	[0.021]	[0.024]	[0.024]
Disaster hits one supplier $(t-4)$	-0.050***	-0.042***	-0.050***	-0.043***	-0.042***	-0.036***
	[0.011]	[0.011]	[0.010]	[0.011]	[0.010]	[0.010]
Disaster hits firm $(t-4)$	-0.015	-0.013	-0.015	-0.014	-0.015	-0.016
	[0.010]	[0.011]	[0.010]	[0.011]	[0.010]	[0.010]
Diverse firm	-0.023	-0.002	-0.017	0.003	0.001	0.015
	[0.018]	[0.017]	[0.022]	[0.019]	[0.021]	[0.019]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	90,941	90,941	90,941	90,941	90,941	90,941
Adjusted R^2	0.209	0.227	0.209	0.227	0.209	0.227

Notes: This table presents estimates for specification (3), but with continuous Herfindahl indexes instead of tercile dummies that measure firms' extent of supply base diversity. Specifically, we regress firms' sales growth relative to the same quarter in the previous year on a dummy indicating if at least one of the firm's suppliers was hit by a disaster four quarters previous, a diversity Herfindahl index, and the interaction of these two variables. The regressions also include a dummy that indicates whether a natural disaster hit the firm and an interaction term between this and the Herfindahl index. Since diverse firms record a value closer to zero in the original Herfindahls, we compute the continuous diversity measures as one minus the indexes $\mathcal{H}, \mathcal{G}$, and $\mathcal{I}$. The regression includes all firm-quarters from 1978 to 2017 in Compustat's Customer Segments dataset. All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and a control variable for the number of suppliers a customer firm has. Columns (2), (4), and (6) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter. Standard errors, represented in square brackets, are clustered at the firm level.* p<0.1; ** p<0.05; *** p<0.01.

Table D1: Do Shocks Propagate When Links Are Not Active?

	(1)	(2)	(3)	(4)
Disaster hits eventually linked supplier $(t-4)$	0.008	0.004	0.004	0.005
	[0.007]	[0.007]	[0.007]	[0.007]
Disaster hits one supplier $(t-4)$	-0.043***	-0.037***	-0.031***	-0.029***
	[0.008]	[0.008]	[0.008]	[0.008]
Disaster hits firm $(t-4)$	-0.021**	-0.014	-0.018*	-0.018*
	[0.009]	[0.010]	[0.010]	[0.010]
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	No	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	No	Yes	Yes
Number of suppliers	No	No	No	Yes
Observations	90,941	90,941	90,941	90,941
Adjusted R^2	0.169	0.208	0.227	0.227

Notes: This table presents estimates of supplier-to-customer propagation when input-output linkages are not active. The variable *Disaster hits eventually linked supplier* $(t-4)$ takes the value one if an eventually (but not currently) linked supplier was hit by a disaster four quarters back and zero otherwise. The dependent variable is real quarterly sales growth. All standard errors are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Appendix D. Additional Empirical Results

Do shocks propagate when links are not active? In Figure 8 and Table 2 we have established that supply shocks propagate to customers. A valid concern is that the reduction in customer firms' sales growth is partly due to the demand effects of major natural disasters. Reduced demand may spill over county and state lines, reducing firm sales growth. If true, we may misattribute the reduction in customer sales to supply-side factors when it stems from demand-side factors. If the decrease in customer sales growth is due to disruptions to their suppliers' production operations, then one should expect the propagation of supply shocks to occur only when the customer-supplier link is active. In other words, we should expect no effect on customer sales when an *eventually linked* supplier (i.e., not currently linked, but linked at some time in the past or future) is hit by a natural disaster.

Table D1 estimates equation (2) but with an additional indicator that takes the value one if an *eventually linked* supplier is hit by a disaster in $(t-4)$, and zero otherwise. This specification allows us to test if shocks propagate even when the customer-supplier relationship is not active. Columns 1-4

Figure D1: Year-On-Year Sales Growth for Diverse and Non-diverse Firms

Note: This figure shows the annual median year-on-year quarterly sales growth for all firms from 1978 to 2017. Firm financial data are from Compustat's *North America Fundamentals Quarterly* dataset. The blue lines represent the sales growth of firms classified as 'diverse' by each of the three corresponding definitions. The red lines represent the sales growth of the firms not classified as 'diverse.' Shaded blue (red) bands depict the interquartile range of diverse (non-diverse) firms' sales growth.

progressively add more controls.

In all four columns, the estimated coefficients for *disaster hits eventually linked supplier* $(t-4)$ are close to zero and insignificant. Concomitantly, the coefficients on *disaster hits supplier* are negative and significant across all specifications, consistent with the results displayed in Figure 8. The placebo test thus shows that the downstream propagation of shocks only occurs when the supplier-customer relationship is active and not otherwise.

Diverse trends. Figure D1 plots the median sales growth for diverse and non-diverse firms for each measure of diversity. The solid blue line represents the median sales growth of diverse firms in each fiscal year, whereas the red line is the median for non-diverse firms. Shaded blue (red) bands depict the interquartile range of sales growth for diverse (non-diverse) firms. The figure shows that diverse and non-diverse firms generally have similar sales dynamics across each year and diversity measure, giving us further confidence that the two groups are not systematically different. Furthermore, since the two series track each other closely for the entire sample period and each diversity measure, we are confident that our results are not being driven by sales growth differences in a few key periods.

Cost of Goods Sold. Sales growth represents both quantity and price effects. Even though sales are adjusted for growth in the GDP deflator, prices may change disproportionately for certain firms, potentially due to demand shocks (which may be correlated with the occurrence of a disaster). This threatens our identification of shock propagation, as the reduction in sales growth would be driven by a fall in prices rather than the quantity of output.

To ensure that it is not price effects precipitating the change in sales growth, we re-run our key regressions by replacing sales growth (which measures the market value of goods sold) with the growth in the cost of goods sold (COGS) as the dependent variable. Overall, the results are largely the same, suggesting that the propagation of shocks from suppliers to customers is driven by customers receiving fewer inputs rather than a lower price for their outputs following a natural disaster. We refer the reader to Barrot and Sauvagnat (2016), who discuss similar robustness tests. Results regarding COGS are available on request.

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