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The Effect of Supply Base Diversification on the Propagation of Shocks

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CAMA Working Paper 60/2022
September 2022
Revised in May 2024

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JEL Classification

D57, E23, E32, L14

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Abstract

We study how supply base diversification affects the propagation shocks. We identify exogenous shocks with the occurrence of natural disasters in the US from 1978-2017. Affected suppliers reduce their customers' sales growth by 30% on average. Notably, firms with input purchases spanning many suppliers, geographies, or producers within industries attenuate the transmission of shocks by 60-70%. We then show, causally, that diverse firms mitigate shocks by temporarily substituting towards unaffected suppliers producing similar inputs. A general equilibrium production networks model reveals that aggregate volatility would have been 33% greater from 1978-2017 in a counterfactual without input substitution by diverse 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 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). In 2020, 83% of semiconductor manufacturers reported that they had experienced disruptions due to Covid-19 lockdowns (Ro, 2020). These disruptions resulted in mass shortages of medical equipment, personal computers, and new automobiles (among other products). While the above examples highlight the potential for significant output losses when firms are overly reliant on a few suppliers, there exists no systematic study that quantifies the effect of supply base diversification on the propagation of shocks.

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 $\approx$ 95,000 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 baseline, we find similar supplier-to-customer propagation effects as other studies in the literature.[2] Specifically, a firm's

[1] Choi and Krause (2006) discuss the disadvantages of a single-sourcing strategy, in which firms that are overly reliant on certain suppliers are exposed to more significant supply risks.

[2] See, for example, Barrot and Sauvagnat (2016), Boehm et al. (2019), and Carvalho et al. (2021).

sales growth decreases by approximately three percentage points if at least one of its suppliers is hit with a natural disaster four quarters back.

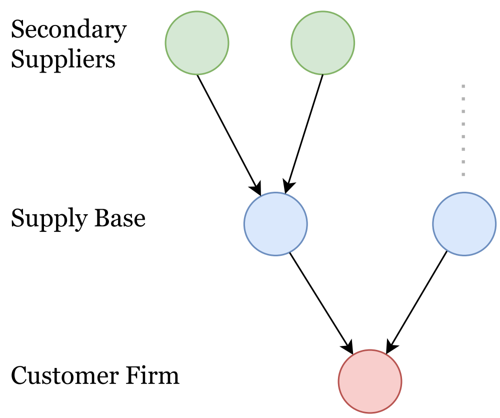

Figure 1: Illustration of a Supply Chain

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.

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] To identify 'diverse' firms, we construct three Herfindahl indexes that measure how a customer firm's total input spending in a given quarter spans: i) all its suppliers (irrespective of their location or industry), ii) US states, and iii) its set of suppliers within 6-digit NAICS industries. The third measure, which we refer to as *intra-industry diversity*, is the purest form of diversity. Firms classified as diverse along this dimension spread their input purchases across multiple suppliers *within* the same industry. As a consequence, these firms can shift their reliance away from affected suppliers towards alternative producers that manufacture similar inputs. Notably, our diversity measures are not firm-specific since a firm's supply base can change over time. Our regressions thus include firm and year-quarter fixed effects, together with other regressors. Our measures of diversity reflect that both regional and sectoral components of the US production network are essential in understanding the spillover effects of local shocks (Caliendo et al., 2017).

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

Across each definition of diversity, we find that diverse firms experience reductions in sales growth that are (on average) 60-70% smaller than non-diverse firms when a major natural disaster hits at least one supplier. Our findings thus support the hypothesis that supply base diversity attenuates the propagation of supply shocks.

An immediate concern is that firms may endogenously choose to be more diversified in response to supply shocks. If firms diversify their supply base when they or their supplier is hit by a disaster, then our estimates may overstate the attenuation effects of diversity. This is because what appears as shock mitigation due to diversity may actually be attributable to other firm characteristics, such as being better prepared for a supply disruption or maintaining higher levels of inventory. We show that supply base diversity is independent of natural disasters. Specifically, firms' level of 'diversity' is not explained by the frequency of disasters hitting customer firms or their suppliers, suggesting that firms do not diversify in response to direct or indirect supply disruptions. The breach of supplier agreements, which may entail costs for customer firms, may act as a deterrent for firms considering reneging on a supply contract. Additionally, search costs may be involved in sourcing inputs from new vendors, which deter firms from switching suppliers.[4]

A related question is whether customers systematically select suppliers based on suppliers' proneness to natural disasters. If customers avoid suppliers in disaster-prone counties, then our estimates will be biased against finding any significant propagation. Nonetheless, we test whether the creation of new customer links or the destruction of existing connections is sensitive to the number of disasters hitting a supplier's county. We find that the number of disasters striking a county does not explain the creation of new links or the destruction of existing connections. This suggests that firms do not systematically base their input-sourcing decisions on suppliers' proneness to disasters.

Another concern is that diversity may be correlated with customers' bargaining power over their suppliers. If affected suppliers first serve their most important customers (diverse firms), the attenuation effects we estimate may actually reflect the benefit of having greater bargaining power and not supply base diversity. To address this, we use a measure of customer firms' bargaining

[4] See Antrás et al. (2017) and Bernard et al. (2019) who discuss search costs involved in finding trade partners.

power from Ahern (2012). We test whether firms with higher bargaining power attenuate shocks relative to firms with lower bargaining power. Importantly, we find that the attenuation effects of diversity remain after controlling for firms' bargaining power.

We also check whether suppliers of non-diverse customers are systematically worse affected by disasters. If so, what may appear as the attenuation of shocks by diverse firms may actually reflect the heterogeneous impact of disasters on suppliers of diverse and non-diverse firms. Crucially, we find that the effect of natural disasters on suppliers' sales growth is orthogonal to the level of diversification of the affected firms' customers, alleviating this concern.

The above checks help establish that the attenuation of shocks is due to firms having an ex-ante diversified supply base and that other explanations are not at play. It is important to clarify, however, that we do not aim to explain *why* firms differ in their level of diversity (after purging out firms' time-varying and time-invariant controls). For example, idiosyncratic factors such as managerial quality and personal connections may generate variation in supply base diversity across firms and even within firms over time. Our objective, instead, is to quantify the impact of diversity on shock propagation. To this end, we establish that the growth in sales of diverse and non-diverse firms exhibits no discernible trends prior to a supply shock, satisfying the parallel trends assumption, and the difference in sales growth (between diverse and non-diverse customers) after a supply disturbance is only temporary in nature.

Why do diverse firms attenuate shocks? There are two possible mechanisms through which diverse firms mitigate shocks. One explanation can be that, for diverse firms, a smaller proportion of their inputs are affected when a disaster strikes a supplier. Second, it is possible that diverse firms can easily substitute towards unaffected suppliers, which prevents a shortfall in their production. While both mechanisms are valid, we distinguish between the two by first controlling for the intensity of shocks experienced by customer firms. We measure the intensity of shocks as the proportion of inputs affected by a disaster. If more "intensely treated" customer firms experience a steeper decline in sales growth, then diverse firms may attenuate shocks simply because only a fraction of their total inputs are disrupted. We find that the treatment intensity does not explain the extent of shock propagation after controlling for at least one supplier being disrupted by a disaster. This implies that the attenuation effects of diversity are not attributed to differences in the share of affected inputs between diverse and non-diverse firms.

To test the substitution mechanism, we explore whether customer firms increase their input purchases from unaffected suppliers following a disruption to another supplier within the same 6-digit NAICS industry. Since suppliers within a narrowly defined industry produce similar, easily substitutable inputs, we would expect to see an increase in expenditure on inputs from unaffected suppliers within the same industry. First, we find that customers' input purchases from an affected supplier decline by approximately two percentage points following a major natural disaster. Second, purchases from unaffected suppliers increase by around three percentage points four quarters after a disaster hits another supplier from the same industry. This coincides exactly when we see the greatest attenuation by diverse firms, suggesting that the propagation of supply shocks is substantially mitigated when customer firms multi-source inputs and can easily substitute across their supply base.[5] Since natural disasters are plausibly exogenous events, we causally identify the mechanism through which diverse firms attenuate supply shocks.

What is the macroeconomic effect of supply base diversity? Our empirical analysis provides evidence that supply base diversity consequentially attenuates supply shocks at the firm level. To quantify the effect of supply base diversity on aggregate output (GDP), we build a general equilibrium model of production networks à la Long and Plosser (1983), and Baqaee and Farhi (2019). In the model, firms use a constant-elasticity-of-substitution (CES) production technology that transforms capital and intermediate inputs into output. Notably, diverse and non-diverse firms differ in their ability to substitute across suppliers in response to upstream shocks and thus have different capacities to attenuate supply disruptions. This aligns with the empirical evidence that diverse firms multi-source inputs and, as a result, can easily switch expenditures towards unaffected suppliers.

We derive a formula that measures the aggregate effect of shock mitigation by diverse firms.

[5] This result is independent of firms' production technology or 'input-mix.' The benefit of diversity in this context emanates from multi-sourcing similar inputs.

The formula compares the level of real GDP volatility with a counterfactual where diverse firms do not substitute across suppliers in response to shocks (and hence behave like non-diverse firms). In this respect, both diverse and non-diverse firms do not attenuate shocks under the counterfactual. Notably, we find that GDP volatility would have been $\approx 33\%$ greater between 1978 and 2017 in the absence of shock attenuation by diverse firms. This quantitative exercise suggests that supply base diversity has substantial macroeconomic effects.

Related literature. Our paper is most closely related to the recent empirical literature that uses natural disasters to establish the propagation of microeconomic shocks through input-output linkages. Barrot and Sauvagnat (2016) show that the transmission of shocks from suppliers to customers 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 instead of 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 discuss in Section 3.3, input specificity and customer diversity are both important drivers of the transmission of supply shocks within the production network. Relatedly, Boehm et al. (2019) study the cross-country transmission of the 2011 earthquake in Japan, showing 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.

Our paper also relates to the theoretical literature that studies the role of input-output linkages as a mechanism through which microeconomic shocks amplify into sizeable aggregate fluctuations. Building on Long and Plosser (1983), studies such as Acemoglu et al. (2012, 2017) and Baqaee and Farhi (2019) characterize conditions under which microeconomic disturbances propagate through the production network to generate fluctuations in aggregate economic variables.[6] We contribute to this literature by quantifying the extent to which diversified firms attenuate fluctuations in aggregate output. The difference between the elasticities of substitution of diverse and non-diverse firms affects how aggregate output responds to shocks in our model. In this sense, we also contribute to the literature that explores the implications of non-unitary elasticities of substitution on the propagation of shocks in production networks (see, for example, Horvath, 2000, Atalay, 2017, and Baqaee and Farhi, 2019).[7,8]

The rest of the paper is structured as follows. Section 2 discusses the data used and provides summary statistics. Section 3 discusses results. Section 4 concludes. Supplementary empirical and theoretical results appear in the Appendix.

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 and 2017.[9] We deflate sales and cost of goods sold (COGS) using the GDP price index from the Bureau of Economic

[6]Early contributions to this topic include Hulten (1978), Jovanovic (1987), Durlauf (1993), and Horvath (1998, 2000). A related set of papers study the role of input-output linkages in propagating shocks in the presence of distortions (see, for example, Bartelme and Gorodnichenko, 2015; Caliendo et al., 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. See Carvalho (2014) and Carvalho and Tahbaz-Salehi (2019) for a thorough review of the literature on production networks.

[7]Papers such as Boehm et al. (2019), 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. Our estimates are broadly consistent with these studies (see Section B.4 in Appendix B for a more detailed discussion).

[8]A separate literature in international trade has studied how global supply chains (GSCs) play a role in shock mitigation (see Baldwin and Freeman, 2022 for a survey of the GSC literature). While the trade literature studies the effects of diversity at the country level, we are the first (to the best of our knowledge) to examine how supply base diversification affects economic activity at the level of the firm.

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

Analysis so that growth in these variables reflects firms' performance, not price dynamics.[10]

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.[11] This avoids a situation whereby a firm (for example) 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 6-digit NAICS 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 NAICS codes to adjust any changes to firms' NAICS over time.

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).[12] Since a firm's location may change over time, we achieve greater veracity by updating 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 period. For observations before 2007, the ZIP code accurate as of the first quarter of 2007 is used. Any residual measurement error would result in firms being incorrectly assigned to a county (un)affected by a natural disaster, which would bias our estimates against finding an effect of natural disasters on firms' sales.

We match the adjusted ZIP codes to the *US ZIP Codes* database, which contains the latitude and

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

[11] This does not mean that the fiscal quarter of a firm must 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.

[12] Naturally, firms may have establishments that are not located in the same county as their headquarters. Measurement error of this kind is likely to bias our estimates against finding an effect of natural disasters on shock propagation. See Barrot and Sauvagnat (2016) for more details.

longitude for all 41,696 private and USPS ZIPs.[13] 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 the 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 A.1 in Appendix A 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.

2.3 Supplier-customer links

The analysis relies on identifying active supplier-customer relationships to establish 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 identity of suppliers and their reported customers, the start and end date of the relationship, and the sales to each customer.[14] One limitation of the Compustat data is that it only contains information on publicly listed firms.

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

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

However, using an alternative dataset, Barrot and Sauvagnat (2016) show that the propagation of supply disruptions is similar across public and private firms. Another limitation is that we only observe a fraction of a firm's total suppliers due to the 10% threshold. Measurement error of this kind means we may miss some cases where a natural disaster hits a customer firm's (unobserved) supplier. However, this implies we may underestimate the extent to which supply shocks propagate to customers, as some observations in the control group are actually treated.

Another issue with the *Customer Segments* files is that reported customer names are often inconsistent with the official company name recorded by Compustat (e.g., "Coca-Cola Co" v.s. "Coca Cola Inc"). In line with Atalay et al. (2011) and Barrot and Sauvagnat (2016), we use a systematic process of 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 $\approx$ 22K unique customer-supplier pairs across $\approx$ 300K customer-supplier-quarter observations. The average supplier-customer relationship in the sample lasts 16 quarters.

The top panel of Figure 2 plots the supplier-customer production network for the first year (1978) and last year (2017) of the sample in a network graph. 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. Additionally, the bottom panel of Figure 2 shows the change in the geographical dispersion of the firm-level production network between 1978 and 2017. Notably, a significant proportion of customer-supplier links are interstate, providing an ideal setting to examine how geographical (supply base) diversity affects the propagation of supply shocks.

We assume supplier-customer linkages are active for all quarters between the first and last time the relationship is recorded in the *Customer Segments* data. This is a conservative approach, as a link may not be active in some of the intermediate years, which would bias our estimates against finding a propagation effect. Finally, we exclude all relationships where the supplier and customer are within a 300-kilometer radius. This allows us to isolate the propagation effect from the demand-

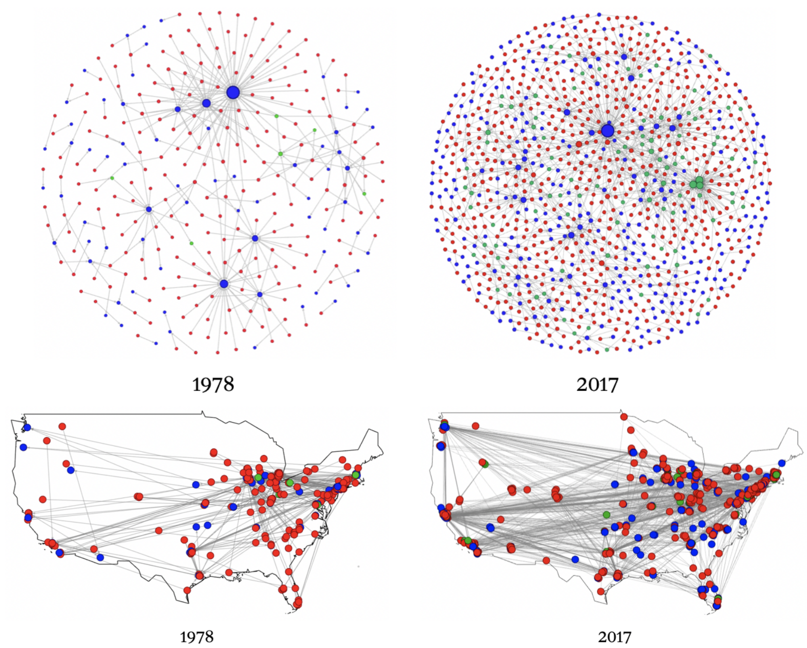

Figure 2: Comparison of US Supply Network (1978 - 2017)

Note: This figure 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. In the top panel, 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). In the bottom panel, 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.

side effect the disaster may have had on the customer firm.[15] The distribution of customer firms' in-degrees (number of suppliers) is positively skewed, with a median supplier count of 10 and a mean of 21.3 (see Appendix Figure A.2). The customer and supplier samples together represent approximately 65% of the total sales of all Compustat firms in the US over the sample period. Therefore, the firms included in our analysis account for a significant proportion of the aggregate activity of public firms in the US.

2.4 Natural disasters

Natural disaster data are compiled from two sources. First, 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

[15] Our results do not change with the inclusion of the 300-kilometer threshold.

damage.[16] EM-DAT records a disaster as an event that meets at least one of the following criteria: (i) 10 or more deaths, (ii) 100 or more people affected, or (iii) a 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, we use the Federal Emergency Management Agency's (FEMA) *OpenFEMA Disaster Declarations* dataset. The FEMA dataset contains all major US Disaster Declarations and Emergency Declarations over the sample period, 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. To this end, we first match disasters based on event names. Where disasters do not have a name, they are matched on the start and end dates, disaster type, and states affected. Where 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, damage estimates, and each event's duration.

In line with Barrot and Sauvagnat (2016), we include all disasters with damages exceeding $1 billion (adjusted to 2017 USD) 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 and 2017, there were 52 major natural disasters. As Appendix Figure A.3 shows, many of these disasters are hurricanes, the most destructive being Hurricane Katrina, with over USD 150 billion in damages. Additionally, most US states were struck at some point in the sample. 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 when the supplier-customer relationship is active. The local 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.

[16] We cross-check damage estimates with publicly reported data for all disaster events and adjust damages for inflation.

2.5 Summary statistics

Table 1 presents summary statistics for the sample of firms used in our analysis. Panel A describes the supplier sample, which includes $\approx$ 5,000 firms generating $\approx$ 180,000 firm-quarter observations between 1978 and 2017. Firms are included in the supplier sample for all quarters from three years before first being recorded as a supplier to three years after last being recorded. In Panel A, 'Eventually Treated' refers to firms directly hit by a major natural disaster at some point in the sample period, and 'Never Treated' refers to those that are not. The mean year-on-year quarterly sales growth for the supplier sample is $\approx$ 19%, although the median is only 4.2%, suggesting a long-tailed distribution. This value is similar across the treated and untreated firms.

Suppliers record an average of USD 1.05 billion in total assets and 4,000 employees. Additionally, among eventually treated suppliers (Panel A), there is a 4% chance a firm will be hit with a disaster in any given quarter ("Disaster hits firm itself (t)"). Of course, the mean for "Disaster hits firm itself (t)" for never treated firms is zero because these firms did not experience a disaster at any point in the sample. The probability a disaster directly strikes a firm is therefore consequentially different between the treated and untreated suppliers.[17] However, the probability that a disaster hits a firm's customer in a given quarter ("Disaster hits customer (t)") is comparable between never treated and eventually treated suppliers at 1.3% and 2.1%, respectively.

Panel B presents the customer sample, comprising $\approx$ 2,000 firms and $\approx$ 95,000 customer-quarter observations. Firms are included in the sample for all quarters from three years before being first reported as a customer to three years after being last reported. Here, '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 disasters have not struck suppliers. There is a near-equal split in the number of firms in the two groups. The primary variable of interest is *sales growth*, measured over four quarters, which is the dependent variable in our main regressions. The average sales growth for eventually-treated and never-treated firms is comparable, at approximately 9% and 12%, respectively. Crucially, firms' sales growth does not predict whether

[17] Across "all" suppliers (Panel A), there is a 2% chance that a disaster will directly strike a firm at quarter t.

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 $(t-4,t)$	85,106	0.21	0.98	94,883	0.18	0.82	179,989	0.19	0.90
COGS growth $(t-4,t)$	83,820	0.22	0.99	93,740	0.18	0.84	177,560	0.20	0.91
Total assets (Bil. USD)	85,106	0.79	2.54	94,883	1.29	3.54	179,989	1.05	3.11
Return on assets	85,106	0.01	0.32	94,883	0.05	0.28	179,989	0.03	0.30
Number of employees ('000s)	82,627	3.39	9.41	93,058	4.58	11.25	175,685	4.02	10.44
Age (Years)	85,106	37.35	18.30	94,883	39.01	19.51	179,989	38.22	18.97
Number of customers	85,106	1.00	1.18	94,883	1.14	1.27	179,989	1.07	1.23
Disaster hits firm itself (t)	85,106	0.00	0.00	94,883	0.04	0.19	179,989	0.02	0.14
Disaster hits customer (t)	85,106	0.01	0.11	94,883	0.02	0.14	179,989	0.02	0.13
Panel B: Customer Sample	Never Treated			Eventually Treated			All		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Sales growth $(t-4,t)$	51,610	0.12	0.45	45,611	0.09	0.33	97,221	0.10	0.40
COGS growth $(t-4,t)$	50,935	0.12	0.49	45,061	0.09	0.38	95,996	0.11	0.44
Total assets (Bil. USD)	51,610	2.71	5.83	45,611	11.89	19.70	97,221	7.02	14.87
Return on assets	51,610	0.10	0.16	45,611	0.14	0.10	97,221	0.12	0.14
Number of employees ('000s)	50,436	10.02	20.21	45,019	37.86	56.25	95,455	23.15	43.60
Age (Years)	51,610	40.64	18.19	45,611	43.54	16.46	97,221	42.00	17.46
Number of suppliers	51,610	0.52	0.88	45,611	3.90	9.02	97,221	2.11	6.44
Disaster hits firm itself (t)	51,610	0.02	0.14	45,611	0.02	0.14	97,221	0.02	0.14
Disaster hits supplier (t)	51,610	0.00	0.00	45,611	0.04	0.19	97,221	0.02	0.13
Avg. distance to supplier ('000 km)	20,253	1.30	1.21	32,589	1.51	0.98	52,842	1.43	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 Segments* dataset. Panel A presents the supplier sample comprising 5,278 distinct firms, creating 179,989 firm-quarter observations from 1978 to 2017. Panel B describes the customer sample. The sample includes 2,256 firms across 97,221 firm-quarter observations.

a disaster will hit a supplier at any point, giving us confidence that firms' performance is exogenous to disasters.

From the mean values of firm *total assets* and *number of employees*, larger firms are more likely to appear in the 'Eventually Treated' group of customer firms (Panel B). This is logical, as larger firms typically have more suppliers and are, thus, more likely to experience supply disruptions. We also observe that the average distance to suppliers is approximately equal for the eventually-treated and never-treated firms in the customer sample. On average, customer firms are located 1,510 km (1,300 km) from their suppliers in the eventually treated (never treated) subgroups. Hence, the distance between suppliers and customers in the two groups is similar. Treated customers are slightly more productive, with an average return on assets (ROA) of 14% compared to 10% for never-treated firms. Additionally, treated customers tend to be older, with an average age of 43.5 years, compared to 40.6 years for never-treated customers. Amongst customer firms, we observe that the incidence of 'Eventually Treated' and 'Never Treated' firms being hit by a major disaster ("Disaster hits firm itself (t)", Panel B) is approximately equal, at 2%. Finally, the probability that a disaster hits the supplier of an eventually treated customer ("Disaster hits supplier (t)") is 4%, implying that between the two subgroups, there is a consequential difference in the chance a disaster strikes a customer's supplier.[18] The differences in size, ROA, age, and supplier count between eventually treated and never treated firms highlight the need to control for these variables.

3 Results

In Section 3.1, we show that natural disasters that represent plausibly exogenous production disruptions not only directly impact suppliers' sales growth but also reduce the sales growth of their customers. In Section 3.2, we define our diversity measures and evaluate how the transmission of shocks differs based on the extent of customers' supply base diversity. In Section 3.3, we rule out some alternative explanations of our results. In Section 3.4, we causally identify the mechanism that explains *how* diverse firms attenuate supply shocks. Finally, in Section 3.5, we discuss the macroeconomic effect of supply base diversity using a general equilibrium production networks model.

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. As discussed in Section 2.4, we identify supply shocks with the occurrence of major natural disasters in the county in which firms' headquarters are located.

There are numerous channels through which a natural disaster could 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

[18] Among "all" customer firms (Panel B), there is a 2% chance a disaster will strike a customer's supplier at quarter t.

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 3.3). This condition allows us to estimate the effect of supply base diversification on the propagation of shocks.

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

$$\Delta\, Sales_{i,t} = \alpha + \sum_{k=-4}^{10} \beta_k Hits\, Firm_{i,t-k} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t}, \tag{1}$$

$$\Delta\, Sales_{i,t} = \alpha + \sum_{k=-4}^{10} \beta_k Hits\, Firm_{i,t-k} + \sum_{k=-4}^{10} \gamma_k Hits\, Supplier_{i,t-k} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t}. \tag{2}$$

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.[19] The indicator $Hits\, Firm_{i,t-k}$ takes the value one when the county in which firm i is located is hit by a natural disaster at time $t+4,\ t+3,\ldots,\ t-10$. 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.[20] 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.[21] Throughout the paper, all regressions include controls for firms' number of employees and age. Finally, we

[19]Consistent with Barrot and Sauvagnat (2016), we re-run regression (2) by replacing sales growth (which measures the market value of goods sold) with 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 suppliers' price dynamics following a natural disaster. See Barrot and Sauvagnat (2016) for details. Results regarding COGS are available on request.

[20]Controlling for firm fixed effects rule out firm-specific characteristics like geographical location, industry, size, and product type to be driving our results.

[21]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).

also control for fiscal-quarter fixed effects.[22] All controls 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 $Hits\ Supplier_{i,t-k}$, which 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 each other, it is still possible that the customer is also simultaneously hit by the same (or some other) natural disaster. 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 $Hits\ Firm_{i,t-k}$.

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 includes a control for the number of suppliers of firm i. 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 3 summarizes the results. The red dashed line captures the direct impact of the disaster on firms (β_k's from Equation 1). Notably, firms experience a significant decrease in sales growth after being hit by a natural disaster, with the maximum decline (-6.4 pp) coming two quarters after the event. The delayed impact of the shock is consistent with what one might expect to occur after a disaster disrupts a firm's production. Firms likely have excess inventory, which buffers the initial effects of reduced production on sales (Hendricks et al., 2009). The estimates are also economically significant; the supplier sample's mean (median) sales growth is 19.2% (4.2%). The estimated 6.4 percentage points decrease in sales growth after two quarters thus represents an approximately 33% decline in average sales growth. Furthermore, exposure to a natural disaster

[22] 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.

lowers the sales growth of affected firms by ≈ 4.3 percentage points after four quarters. Our results establish the negative impact of major natural disasters on firms directly affected by these supply shocks.

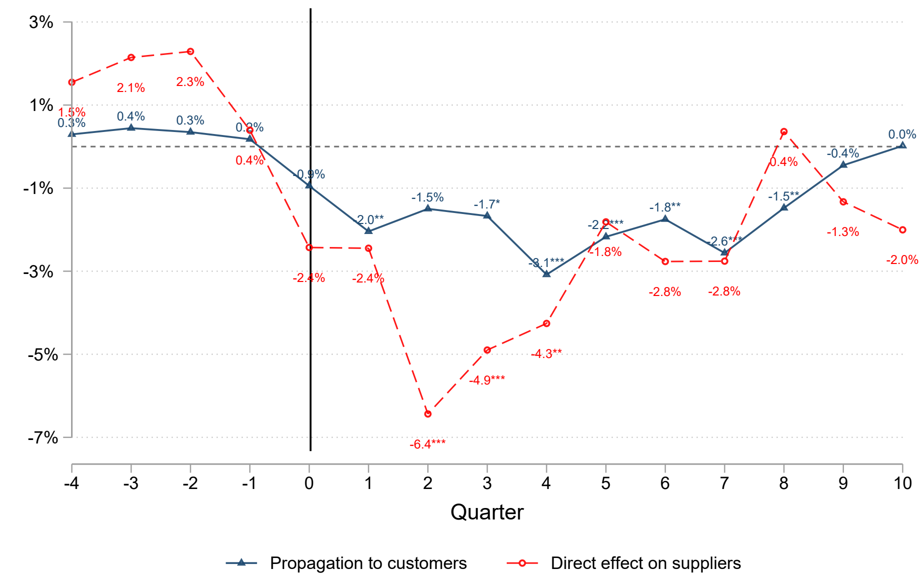

Figure 3: Propagation of Shocks From Suppliers to Customers

Note: This figure shows the average effect of natural disasters on firms' sales growth (red dashed line) and the propagation of shocks to affected firms' customers (solid blue line). The dashed line shows β_k's from Equation (1). whereas the solid line displays γ_k's from Equation (2). Standard errors are clustered at the firm level. *10%; **5%; ***1% significance levels.

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 3 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 3.1 percentage point drop. This amounts to a 31% decline in average sales growth in the customer sample. Indirectly affected customers recover slowly, returning to pre-shock sales growth nine 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. These baseline results establish that production disruptions propagate from suppliers to customers.[23] Additionally, our results align with existing

[23]Figure 3 also shows that it is not pre-existing trends driving the change in customer sales growth but rather the

literature on the topic.[24,25]

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 item *salecs*. 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. Since firms' financial information varies at the firm-quarter level, we convert *salecs* to a quarterly variable by assuming annual purchases are evenly distributed across all four quarters in a given year. It is important to note that we estimate diversity based on firms' first-tier (as opposed to direct *and* indirect) suppliers. The rationale is that these suppliers are chosen by customers, meaning our diversity measures reflect strategic input-sourcing decisions by firms. While businesses know their primary suppliers, they often have little or no knowledge of their second or higher-order suppliers (Farrell and Newman, 2022). Thus, they have limited control over the composition of their entire supply chain. For this reason, we focus on diversity across firms' supply base and abstract from more systemic measures that account for firms' higher-order suppliers. However, we consider this to be an important avenue for future work.[26]

Measuring diversity. We define three Herfindahl indexes that measure the degree of concentration of a firm's purchases over i) its suppliers, ii) geographies, and iii) producers within industries in a given quarter. The first measure captures the extent to which a customer firm's total input

effects of the shock.

[24]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.

[25]Appendix Table A.1 presents estimates for 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 whether supplier shocks affect customer firms even when the customer-supplier relationship is not active. Columns 1-4 progressively add more controls. In all specifications, the estimated coefficients for *disaster hits an eventually linked supplier* $(t-4)$ are close to zero and insignificant. Furthermore, the coefficients on *disaster hits one supplier* $(t-4)$ are negative and significant across all specifications, consistent with the results displayed in Figure 3. Our results are also robust to changing the threshold (of 300 km) at which we exclude customer-supplier relationships.

[26]See Elliott et al. (2022) who study the fragility of the entire supply network to idiosyncratic failures of individual supply relationships. Relatedly, see Carvalho et al. (2022) for a discussion on bottleneck firms.

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, where lower values 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 classify firms as diverse using an indicator $DiverseFirm^{\mathcal{H}}_{i,t}$ 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.

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

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

where $Purchases_{st,t}$ is the value of purchases a customer makes from supplier(s) in state st and quarter t. If a customer firm has multiple suppliers 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 $\mathcal{G}_{i,t}$ imply that i's input purchases are distributed across multiple states. A value $\mathcal{G}_{i,t} = 1$ means 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 $DiverseFirm^{\mathcal{G}}_{i,t} = 1$ for these firms. Non-diverse firms are assigned a value of zero.

Finally, we measure supply base diversity based on how i allocates its input purchases across suppliers within 6-digit NAICS industries. Specifically, i's intra-industry diversity $\mathcal{I}_{i,t}$ in quarter t

is measured as:

$$\mathcal{I}_{i,t} = \sum_{k \in I} \alpha_{k,t} \sum_{j \in I_k} \left\{ \frac{Purchases_{j,t}}{Purchases_{k,t}} \right\}^2 .$$

In the above equation, I is the set of 6-digit NAICS industries from which firm i sources inputs during quarter t, and I_k denotes the set of suppliers within industry k. $Purchases_{j,t}$ represents firm i's purchases from supplier j within industry k, and $Purchases_{k,t}$ is firm i's total purchases from all suppliers within industry k. Finally, $\alpha_{k,t}$ measures the proportion of i's total expenditure allocated to industry k during quarter t.

We view $\mathcal{I}_{i,t}$ as the purest measure of supply base diversity since firms with low values of $\mathcal{I}_{i,t}$ spread their input purchases across multiple suppliers within narrowly-defined industries. As a consequence, these firms have the capacity to shift their reliance away from affected suppliers towards alternative producers that manufacture similar inputs. Indeed, in Section 3.4, we show that customer firms, when faced with a disruption affecting at least one supplier within the same 6-digit NAICS industry, substitute their input purchases towards alternative, unaffected suppliers in that industry. When $\mathcal{I}_{i,t} = 1$, firm i acquires all its recorded inputs from a single firm within each supplier industry. As above, we define firms in the lowest tercile of $\mathcal{I}$ as diverse and assign the indicator $DiverseFirm^{\mathcal{I}}_{i,t}$ a value of one for these firms. As with our other measures, we assign non-diverse firms a value $DiverseFirm^{\mathcal{I}}_{i,t} = 0$.[27]

Shock propagation and diversity. We now estimate the extent to which supply shocks propagate from suppliers to customers when the customer firm is diverse relative to when it is not. To test this, we run the following specification:

$$\begin{aligned} \Delta\, Sales_{i,t} \; &= \alpha + \beta \cdot Hits\ Firm_{i,t-4} + \gamma \cdot Hits\ Supplier_{i,t-4} + \delta \cdot Diverse\ Firm_{i,t} \\ &\quad + \kappa \cdot Hits\ Supplier_{i,t-4} \times Diverse\ Firm_{i,t} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

which is the same as Equation (2) but with two additional regressors. The variable $Diverse\ Firm_{i,t}$

[27] It is important to understand how the 10% reporting rule discussed in Section 2.3 affects how we measure supply base diversity. In Section 3.3, we discuss why the 10% reporting rule is unlikely to be a cause for concern as it works against finding any impact of diversity on shock propagation.

represents one of the three diversity indicators. We run separate regressions for each definition of diversity and omit the superscript for notational convenience. The interaction $Hits\ Supplier_{i,t-4}$ $\times Diverse\ Firm_{i,t}$ takes a value of one if a natural disaster hits a diverse firm's supplier. To keep the model tractable and parsimonious, we estimate Equation (3) when the natural disaster strikes the firm or its supplier at lag four when the indirect impact of natural disasters is the most pronounced.[28] The coefficient of interest, κ, estimates the average difference in sales growth of diverse and non-diverse firms when at least one supplier is hit by a natural disaster.

Our diversity indicators may be correlated with the size of the customer firms, i.e., larger firms have multiple suppliers. Firm fixed effects and controls for firm size ensure that coefficients on the diversity variables reflect the impact of customer diversity, not size. Additionally, since diverse firms (on average) have more suppliers than non-diverse firms, we control for firms' number of suppliers in our regressions. Table 2 reports different versions of Equation (3). We estimate the impact of customer diversity as measured by $DiverseFirm^{\mathcal{H}}$, $DiverseFirm^{\mathcal{G}}$, and $DiverseFirm^{\mathcal{I}}$ in columns 1–2, 3–4, and 5–6, respectively. Columns 2, 4, and 6 report results with all controls included in Equation (3).

A disaster hitting the customer firm reduces its sales growth by approximately two percentage points after four quarters, as shown by the estimated coefficients on *disaster hits firm* in Table 2. This finding is broadly consistent with our estimates in Figure 3, whereby the direct impact of natural disasters largely subsides after four quarters. The key difference is 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 60-70% 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, $DiverseFirm^{\mathcal{H}}$. In column 2, with all controls, the estimated coefficient on *disaster hits one of diverse firm's supplier*

[28] Our results hold when we control for various leads and lags of *Hits Firm*, *Hits Supplier*, and the interaction of *Diverse Firm* with *Hits Supplier* as shown in Appendix Figure A.4.

Table 2: The Effect of Supply Base Diversity on Shock Propagation

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.037***	0.026**	0.040***	0.031**	0.036***	0.028**
	[0.013]	[0.013]	[0.013]	[0.013]	[0.012]	[0.012]
Disaster hits one supplier $(t-4)$	-0.050***	-0.042***	-0.051***	-0.045***	-0.044***	-0.039***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]	[0.010]
Disaster hits firm $(t-4)$	-0.016	-0.020**	-0.016	-0.020**	-0.016	-0.020**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.016*	-0.005	-0.021**	-0.011	-0.029***	-0.018*
	[0.009]	[0.008]	[0.009]	[0.008]	[0.010]	[0.010]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Age & number of employees controls	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	95,455	95,455	95,455	95,455	95,455	95,455
Adjusted R^2	0.202	0.220	0.202	0.220	0.202	0.220

Notes: This table presents estimates relating to regression specification (3). 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 control variables for firms' number of suppliers, number of employees, and age. Columns (2), (4), and (6) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter indicators. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

$(t-4)$ is 0.026, significant at the 5% level. This implies the drop in sales growth following a supplier being hit by a disaster is 2.6 percentage points lower for diverse firms. Where a non-diverse firm's sales growth drops by an average of 4.2 percentage points, a diverse firm's sales growth falls by a statistically insignificant 1.6 percentage points ($p-value\ = 0.08$). This result is economically significant, representing 62% attenuation of the shock.

Customers 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 3.1 percentage points (significant at the 5% level) less than their non-diverse counterparts. Specifically, the sales growth of geographically diverse firms falls by a statistically insignificant 1.3 percentage points ($p-value\ = 0.13$), compared to 4.5 percentage points for non-diverse firms. This amounts to a 69% 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 intra-industry diversity measure are also 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. Specifically, the estimate in our preferred specification (column 6) is 2.8 percentage points, significant at the 5% level. Firms identified as diverse according to intra-industry dispersion experience a decline in sales growth of a statistically insignificant 1.1 percentage points ($p-value\ = 0.22$) following a supply shock, compared to 3.9 percentage points for non-diverse firms. This finding translates to 72% attenuation of the impact of the shock, which is the largest of the three measures.

The above results suggest that firms that have a diverse supply base are more resilient against supply chain shocks.[29] As discussed above, we hypothesize that the mechanism through which diverse firms attenuate shocks is via substitution towards unaffected suppliers. In Section 3.4, we provide evidence supporting this hypothesis, showing that customer firms *increase* input purchases from unaffected suppliers following a shock to at least one other supplier from the same industry.[30]

The variation we use to identify the attenuation effect of supply base diversity is seemingly idiosyncratic. Appendix Figure A.7 shows that our diversity measures are orthogonal to various firm attributes one might expect to influence firms' input-sourcing decisions.[31] Of course, there may be unobserved characteristics that can explain this residual identifying variation in firms' supply base diversity. For example, managers' industry connections may influence input sourcing decisions. We do not aim to explain all of the identifying variation in diversity across firms. Instead, it is sufficient for us to check whether diverse and non-diverse firms exhibit parallel trends, i.e., the

[29] We test whether our findings in Table 2 are robust to the inclusion of extra controls. Appendix Figure A.5 presents estimates for specification (3) but with the progressive inclusion of firm, time, size, return on assets (ROA) by quarter, state-time, and industry-time fixed effects and a level of inventory control. Our key empirical finding that diverse firms attenuate shocks is robust to the inclusion of these additional controls.

[30] Intra-industry diverse firms, on average, source inputs from 2.22 (median = 1.83) suppliers within a 6-digit NAICS code. Approximately 80% of diverse firms multi-source inputs from at least two suppliers within the same industry. In contrast, non-diverse firms, on average, source inputs from 1.11 (median = 1) suppliers within a 6-digit NAICS code. See Appendix Figure A.6 for the distributions of supplier counts within 6-digit NAICS industries.

[31] Specifically, we regress each diversity indicator on a different firm characteristic and all controls shown in Table 2. As shown in Appendix Figure A.7, we do not find any significant correlation between our diversity measures and firms' number of employees, level of inventory, R&D investment, selling, general, and administrative (SG&A) spending, and property, plant and equipment (PP&E) expenditure.

firms in the two groups are not systematically different (on average) over any other characteristic, except supply base diversity.

To test this, we analyze the dynamics of the effects of supply shocks on sales growth in Appendix Figure A.4. We extend specification (3) by including four leads and ten lags of each key regressor. The regressions presented in Figure A.4 also include all controls in Table 2. In Figure A.4, blue (red) estimates correspond to the propagation effect on diverse (non-diverse) customer firms' sales growth when at least one supplier is affected by a disaster at time $t+4$ to $t-10$.[32] For each diversity measure, diverse and non-diverse firms have near-identical sales dynamics prior to a disaster hitting a supplier. Non-diverse firms then experience a substantial drop in sales growth after four quarters (between 3.9-4.6 pp) and then recover nine quarters after the initial shock.

In contrast, diverse firms experience a decline in sales growth of only 1.0-1.4 percentage points (insignificant at the 10% level) four quarters following a supplier disruption. This is followed by a modest sales growth decline of 1.9-2.4 percentage points five quarters after the shock before recovering one quarter earlier than their non-diverse counterparts (i.e., at $t+8$). These results confirm that the attenuation of the supply shocks by diverse firms is not attributable to pre-existing trends. The sales growth dynamics before the shock suggest that diverse and non-diverse firms are not systematically different, except in the extent of their supply base diversity.

3.3 Discussion

In this section, we address some important concerns relating to our results in Section 3.2. Our broad objective is to highlight that the attenuation effects estimated in Table 2 are not explained by confounding factors. Specifically, we address the following questions: 1) How does the customer reporting threshold in Compustat affect our estimates? 2) Is supply base diversity independent of disasters? 3) Are supplier-customer links endogenous to disasters? 4) Are suppliers of diverse customers less affected by disasters? 5) Is customer diversity correlated with suppliers' input-

[32] In Table 2, the coefficient on *disaster hits one of diverse firm's suppliers* measures the *attenuation* effect attributable to diversity. In Figure A.4, we show the *propagation* effect on diverse firms' sales growth (i.e., $(\hat{\gamma}+\hat{\kappa})$ in Equation 3).

specificity? After addressing these concerns, we *causally* identify the mechanism that explains *how* diverse firms attenuate shocks in Section 3.4.

How does the customer reporting threshold affect our estimates? A possible concern is that due to the 10% reporting threshold, we incorrectly identify firms as diverse when they are non-diverse (or vice-versa). This is unlikely to threaten our findings for two reasons. First, using the same data as us, Atalay et al. (2011) find the fraction of unobserved suppliers is statistically similar across customers with many or few suppliers. This finding is important in the context of our study since it implies that the Herfindahls $\mathcal{H}$,$\mathcal{G}$ and $\mathcal{I}$ correctly rank firms by their level of diversity as long as purchases are evenly spread across missing suppliers. Second, any remaining measurement error (across each definition of diversity) will bias our estimates against finding an effect of diversity on shock propagation.[33] This is because the attenuation of shocks by some truly diverse firms will be incorrectly attributed to the group of non-diverse firms. Similarly, some truly non-diverse firms may be incorrectly attributed to the group of diverse firms. Overall, such measurement error will dilute the difference in sales growth between the two groups of firms. For this reason, we view our estimates in Table 2 as a lower bound of the attenuation effects of supply base diversification. Nonetheless, as an additional check, we test whether our results are robust to the inclusion of continuous diversity measures instead of indicators. This further alleviates the concern that we misclassify firms as diverse or non-diverse. Appendix Table A.3 presents estimates of Equation (3) but where *Diverse Firm* is a continuous (instead of a dummy) variable. Across the three diversity measures, the coefficient on *disaster hits one of a diverse firm's suppliers* $(t-4)$ implies that a one standard deviation increase in diversity (as measured by the Herfindahls defined above) corresponds to an attenuation effect of $\approx$ 1.1 to 1.4 percentage points, which is consistent with our estimates in Table 2.

Relatedly, given the 10% reporting threshold, one may be concerned that "high supply base diversity" is observed for large firms buying inputs from small suppliers, over which they may

[33]To show this, we re-run specification (3) after randomly identifying customers as diverse. Appendix Table A.2 presents the results. In this exercise, we find no effect of supply base diversity on the propagation of shocks across all specifications, highlighting that measurement error underestimates the positive impact of diversity.

have greater bargaining power. If affected suppliers first serve their most important customers, the attenuation effects we estimate in Table 2 may actually reflect the benefit of having more bargaining power over suppliers and not the benefits of supply base diversity. In Appendix Table A.4, we augment regression (3) to control for firms' level of bargaining power using the measure defined in Ahern (2012).[34] Our findings suggest that firms with greater bargaining power do not mitigate shocks compared to firms with lower bargaining power. Notably, regardless of the specification, the attenuation effect of supply base diversity on shock propagation remains significant when we control for firms' bargaining power.

Is supply base diversity independent of disasters? If firms diversify their supply base when a disaster hits an existing supplier, the estimates presented in Table 2 could potentially overstate the attenuation effects of diversity. This is because what appears as shock mitigation due to diversity may actually be attributable to other firm characteristics, such as being better prepared for a supply disruption or maintaining higher levels of inventory. We test whether supply base diversity is independent of disasters. Specifically, we run the following regression

$$\begin{aligned} HHI^{\mathcal{D}}_{i,t} &= \alpha + \#\, \textit{Supplier Disruptions in Past Five Years}_{i,t} \\ &\quad + \#\, \textit{Disasters in Past Five Years}_{i,t} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where $HHI^{\mathcal{D}}_{i,t}$ is the Herfindahl of firm i in quarter t and where $\mathcal{D} = \{\mathcal{H}, \mathcal{G}, \mathcal{I}\}$ indexes the type of diversity discussed in Section 3.2. We regress each type of Herfindahl on the number of *supplier disruptions* a firm experienced in the past five years and the number of disasters the firm *itself* experienced in the past five years. In addition, we also include the same controls $\mathbf{X}_{i,t}$ as specification (3) as well as time τ_t and firm η_i fixed effects.

The results relating to regression (4) are presented in Appendix Table A.5. First, we find firms' level of diversity to be orthogonal to the number of disasters the firm *itself* experienced in the

[34] Specifically, we measure a customer firm's bargaining power over its supplier by first calculating the ratio of the customer's purchases from its supplier to the supplier firm's total sales. We then compute bargaining power in quarter t by taking a weighted average of this ratio across all suppliers.

past five years. The estimated coefficient on the number of disasters directly striking customer firms is near zero for each diversity measure. Crucially, the number of supplier disruptions in the previous five years also does not predict firms' level of diversity across each of our measures. The estimated coefficients on the *number of supplier disruptions in the past five years* are statistically insignificant and near-zero across each specification, implying firms do not diversify when their suppliers experience shocks.[35]

Are supplier-customer links endogenous to disasters? We go one step further and 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 3 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. We estimate the following specifications

$$\#\ New\ Links\ Created_{county,t} = \#\ of\ Disasters_{county,(t-5,\ t)} + \tau_t + \gamma_{county} + \varepsilon_{county,t} \tag{5}$$

$$\#\ Old\ Links\ Destroyed_{county,t} = \#\ of\ Disasters_{county,(t-5,\ t)} + \tau_t + \gamma_{county} + \varepsilon_{county,t}. \tag{6}$$

Equations (5) and (6) have a unit of observation as a county-year. Equation (5) 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 (6) 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 Appendix Table A.6 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

[35] Regressions involving the Herfindahls measure whether disasters (direct or indirect) affect the level of supply base diversity at the intensive margin. We also find firm diversity to be independent of disasters along the extensive margin (where the outcome variables are the diversity indicators). Results are available upon request.

of existing connections. It is worth noting that there is substantial variation in the number of new links created and destroyed across counties and over time.[36] Hence, the insignificance of results is not due to the lack of variation in the regressands.

Overall, these results suggest that firms' supply networks are rigid, as in Kinnan et al. (2024). Specifically, customer firms seemingly do not base input-sourcing decisions on suppliers' proneness to disasters. It is worth noting that while we leverage natural disasters as exogenous supply shocks, firms often face many kinds of supply disruptions in the form of political, transport, natural, and technological disasters. In choosing suppliers, the price and quality of inputs may be more important determinants relative to suppliers' proneness to a particular type of supply shock. Additionally, sunk costs involved in searching for and selecting suppliers may further deter customers from reacting to *temporary* supply disturbances (Antrás et al., 2017; Bernard et al., 2019).

Are suppliers of diverse customers less affected by disasters? It is important to consider whether natural disasters impact suppliers of diverse and non-diverse customers differently. For example, 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 the observed attenuation effects of diversity may be due to the heterogeneous impact of disasters on suppliers of diverse and non-diverse firms. Appendix Table A.7 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 is identified as diverse anytime between $(t-1)$ to $(t-4)$ and zero otherwise. We regress suppliers' 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. Under all

[36]The mean number of new links created in a given year is 0.18 (s.d. = 1.45), with a maximum of 72 relationships formed. Similarly, the mean number of relationships destroyed in a year is 0.18 (s.d. = 1.40), with a maximum of 71 links. Furthermore, the number of disasters hitting a given county over a five-year period ranges between 0 and 9, with a mean of 0.44 (s.d. = 0.89).

three definitions of diversity, the coefficients on *Natural disaster hits firm with a diverse customer* $(t-1, t-4)$ are statistically insignificant and close to zero. The estimates for the impact of a natural disaster on firms' sales growth, given by the coefficients on *Natural disaster hits firm* $(t-1, t-4)$ (second row), are consistent with estimates displayed in Figure 3. 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).

Is customer diversity correlated with suppliers' input-specificity? In a recent paper, 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 share of differentiated (i.e., nonhomogeneous) goods lies above the median 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. Relative to non-specific suppliers, Barrot and Sauvagnat find customers' sales growth to decline by an additional 3-4 percentage points if a natural disaster hits a 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 attributable to supply base diversity but to the absence of specific inputs for such customers. In Appendix Table A.8, we check how the results reported in Table 2 change if we control for input specificity.[37] Table A.8 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 A.8, we define supplier specificity

[37] 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 Appendix Table A.8, which explains the lower number of observations relative to Table 2.

based on patents. The results are qualitatively the same when we use Rauch (1999) and R&D as measures of input specificity.[38]

Consistent with Table 2, Table A.8 shows that: i) a disaster affecting a firm decreases its customers' sales growth by $\approx$ 4-5 percentage points after four quarters (row 3), and ii) having a diverse supply base attenuates supply shocks by approximately 3-4 percentage points (row 1). Finally, in line with Barrot and Sauvagnat (2016), input specificity does amplify supply shocks. If a specific supplier is hit with a disaster (row 2), its customers experience an additional three percentage points decline in sales growth after four quarters. Overall, the results show that supply base diversity and input specificity are both key drivers of how shocks propagate from suppliers to customers. While suppliers' input specificity amplifies the transmission, customers' supply base diversity attenuates it.

3.4 Why do diverse firms attenuate shocks?

Diverse firms may attenuate shocks either because i) a smaller proportion of their input supplies are affected when a disaster strikes a supplier or ii) they can substitute across suppliers more easily, which prevents a shortfall in their production. While both are valid mechanisms through which diverse firms benefit, we distinguish between the two by first controlling for the intensity of the shocks experienced by customer firms. We define shock intensity as the share of customer firms' total intermediate input use disrupted by disasters. Formally,

$$Shock\ Intensity_{i,t-4} = \sum_{s} \frac{\text{Purchases}_{s,t-4}}{\text{Purchases}_{i,t-4}} \times \text{Supplier } s \text{ Hit by a Natural Disaster}_{t-4},$$

where $\text{Purchases}_{s,t-4}$ is the nominal value of input purchases from supplier s in quarter $t-4$, $\text{Purchases}_{i,t-4}$ is i's total value of purchases at $t-4$ and Supplier s Hit by a Natural Disaster_{t-4} is an indicator that takes the value one if supplier s was struck with a natural disaster. The larger the value of $Shock\ Intensity$, the more intensely treated is the customer firm since a greater proportion

[38] Results for Rauch and R&D specificity measures are available on request.

of its input use is affected by supply shocks. If more "intensely treated" customer firms experience a steeper sales growth decline, diverse firms may attenuate shocks simply because only a fraction of their total inputs are disrupted. In contrast, if the intensity of the supply shock does not matter for customers' sales growth, diverse firms likely attenuate shocks by shifting their input purchases towards other suppliers (i.e., the substitution channel is more prominent). To test this, we run the

Table 3: Downstream Propagation with Weighted Shocks

	(1)	(2)	(3)	(4)
Intensity of shock $(t-4)$	0.006	0.015	0.013	0.010
	[0.021]	[0.020]	[0.020]	[0.020]
Disaster hits one supplier $(t-4)$	-0.027***	-0.041***	-0.037***	-0.033***
	[0.008]	[0.008]	[0.008]	[0.008]
Disaster hits firm $(t-4)$	-0.013	-0.016	-0.020**	-0.020**
	[0.009]	[0.010]	[0.010]	[0.010]
Age & number of employees controls	Yes	Yes	Yes	Yes
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 control	No	No	No	Yes
Observations	95,455	95,455	95,455	95,455
Adjusted R^2	0.172	0.201	0.220	0.220

Notes: This table presents estimates relating to regression specification (7). The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects, fiscal quarter fixed effects, and control variables for firms' number of employees and age. Columns (2), (3), and (4) progressively add year-quarter fixed effects, size and ROA interacted with year-quarter fixed effects, and a number of suppliers control, respectively. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

following regression:

$$\Delta\, Sales_{i,t} = \alpha + \beta \cdot Hits\ Firm_{i,t-4} + \gamma \cdot Hits\ Supplier_{i,t-4} + \delta \cdot Shock\ Intensity_{i,t-4} + \mathbf{X}_{i,t} + \tau_t + \eta_i + \varepsilon_{i,t}. \quad (7)$$

The coefficient of interest is δ, which captures the effect of supply shock intensity on shock propagation when at least one supplier was hit by a shock four quarters back. Table 3 presents the results relating to regression (7). Specifically, the coefficient on *Shock Intensity* is statistically insignificant across all specifications, meaning that differences in treatment intensity do not influence the extent of shock propagation to customer firms. Furthermore, the coefficient on *disaster hits one supplier* is statistically significant at the 1% level across each regression and is comparable in magnitude to our estimate presented in Figure 3 (-3.1pp). These results indicate that the effects of diversity shown in Table 2 are not attributable to differences in treatment intensity between diverse and non-diverse firms and suggest that substitution between inputs insulates diverse firms against upstream shocks.

To test the latter hypothesis, we explore whether customer firms increase their input purchases from unaffected suppliers within a 6-digit NAICS industry following a disruption to another supplier within the same industry. Suppliers within a narrowly defined industry produce similar, easily substitutable inputs. Thus, if firms indeed substitute in response to supplier shocks, we would expect to see an increase in expenditure on inputs from unaffected suppliers within the same industry. To test this formally, we run the following regression:

$$\begin{aligned} \Delta\, Input\ Purchases_{ij,t} &= \alpha + \sum_{k=-4}^{10} \beta_k Affected\ Supplier_{ij,t-k} \\ &+ \sum_{k=-4}^{10} \gamma_k Unaffected\ Supplier_{ij,t-k} + \sum_{k=-4}^{10} \kappa_k Hits\ Firm_{ij,t-k} + \mathbf{X}_{ij,t} + \tau_t + \eta_i + \varepsilon_{ij,t} \quad (8) \end{aligned}$$

where $\Delta\ Input\ Purchases_{ij,t}$ is the growth rate of customer firm i's real input purchases from supplier j between t and $t-4$. $Affected\ Supplier_{ij,t-k}$ is a dummy that takes the value one if supplier j of customer i was hit by a shock in quarter $t-k$. $Unaffected\ Supplier_{ij,t-k}$ is a dummy that takes the value one if i has a supplier j that was not hit by a disaster *and* there exists at least one *other* supplier of i (from the same 6-digit NAICS industry as j) that was hit by a disaster in quarter $t-k$. As above, we also control for $Hits\ Firm_{ij,t-k}$ to avoid confounding the effect of a supplier being hit by a disaster with the direct effect of the disaster on a customer firm. Finally, Equation (8) includes all additional controls in Table 2 as well as supplier industry fixed effects.

The results are shown in Figure 4. The red dashed line represents the impact on input purchases from affected suppliers (the β_k's in Equation 8) for up to 10 quarters following a disaster. In

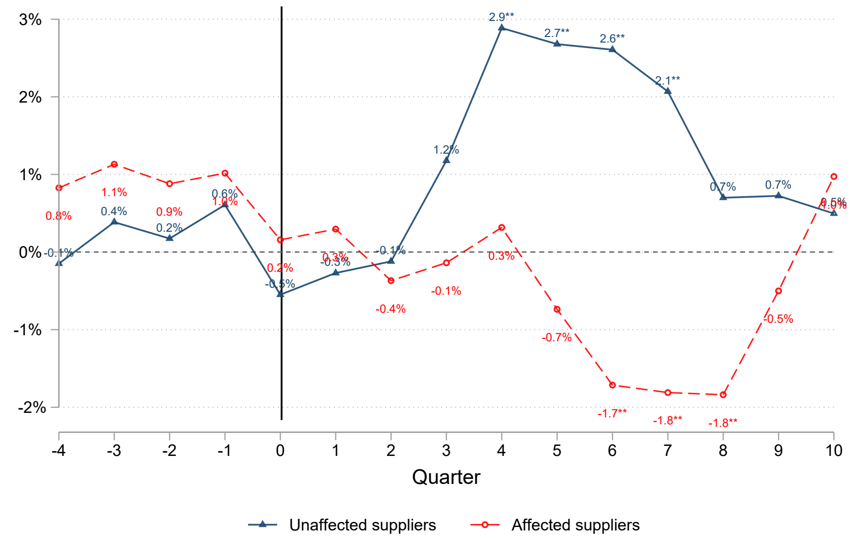

Figure 4: Substitution Towards Unaffected Suppliers

Note: This figure shows estimates relating to regression specification (8). The red estimates show the average change in input purchases from suppliers hit by a major natural disaster in period $t-k$. The blue estimates show the average change in input purchases from unaffected suppliers within a 6-digit NAICS industry at time $t-k$. Standard errors are clustered at the customer firm level. *10%; **5%; ***1% significance levels.

contrast, the blue solid line shows the change in input purchases from unaffected suppliers over the same horizon (γ_k's in Equation 8). Notably, purchases from unaffected suppliers within a 6-digit NAICS code increase by $\approx$ 3pp four quarters after a disaster hits another supplier from the same industry. This coincides exactly when we observe the greatest attenuation by diverse firms in Appendix Figure A.4, suggesting that the propagation of supply shocks is substantially mitigated when customer firms multi-source inputs and can substitute across similar suppliers.

Concurrently, we observe a significant decline in input purchases from affected suppliers. The maximum decline occurs six quarters after a supplier is affected by a disaster, where input purchases decrease by approximately two percentage points. Interestingly, this reduction in sales does not exactly coincide with the increase in purchases from unaffected suppliers (i.e., at $t+4$). This *may* be explained by an increase in the price of inputs produced by affected suppliers, where the quantity effect dominates after a lag. Irrespective, Figure 4 shows there is a significant drop in purchases from affected suppliers following a negative supply shock. Overall, the results suggest that customer firms *temporarily* substitute inputs away from affected to similar unaffected suppliers, where input purchases return to normal after roughly two years. Since the treatment in Figure 4 is suppliers being disrupted by exogenous disasters, our results causally identify the mechanism through which diverse firms attenuate supply shocks.

3.5 The macroeconomic effect of supply base diversity

Our empirical findings reveal that supply base diversity has a significant impact on shock propagation at the firm level. In Appendix B, we estimate the macroeconomic effect of the substitution behavior of diverse firms, as shown empirically in Figure 4. In other words, we estimate the aggregate impact of diverse firms minimizing production losses by substituting inputs in response to shocks to their suppliers.

To do so, we first build a general equilibrium model of production networks in the spirit of Acemoglu et al. (2012) and Baqaee and Farhi (2019). We assume both diverse and non-diverse firms have constant-returns CES production functions. Noting that diverse firms multi-source similar inputs of production and are able to easily substitute between them, we estimate different elasticities of substitution between inputs for diverse and non-diverse firms: $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$, respectively.[39,40]

We estimate $\theta_{\mathcal{D}} = 3.206$, suggesting a high degree of substitutability between inputs for diverse firms, on average. For non-diverse firms, $\theta_{\mathcal{N}}$ is not statistically different from one, suggesting a Cobb-Douglas production technology. Our elasticity estimates are comparable to the ones reported in Oberfield and Raval (2021); Peter and Ruane (2020) and Carvalho et al. (2021).

With the estimates of elasticities of substitution $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ in hand, we use the model to quantify the macroeconomic effect of capital-augmenting microeconomic shocks due to natural disasters. We show that the change in GDP can be decomposed into the first- and second-order effects of the shocks, and that all second-order effects are solely attributable to diverse firms substituting

[39] In line with Carvalho et al. (2021), we model natural disasters as capital-augmenting shocks that result in the reduction of disaster-affected firms' operable capital.

[40] We assume each firm produces a distinct product, i.e., all intermediate inputs are distinct. Understandably, similar inputs from the same industry are likely to be more substitutable than inputs across industries. The elasticities $\theta_{\mathcal{N}}$ and $\theta_{\mathcal{D}}$ measure how substitutable an input is with other inputs, *on average*. Clearly, if diverse firms multi-source inputs from different industries, then their average elasticity across inputs would be higher relative to firms that single-source inputs from different industries.

inputs away from disaster-affected suppliers.

Overall, the substitution behavior of diverse firms attenuates the impact of natural disasters on *aggregate* output. To estimate the macroeconomic effect of diversity, we compare the model-implied level of GDP volatility with a counterfactual where diverse firms do not substitute (and thus act like non-diverse firms). That is, we assume both $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ to be equal to one, and we re-estimate the change in GDP in response to the same vector of shocks.[41] Our counterfactual analysis reveals that aggregate output would have been $\approx 33\%$ more volatile between 1978 and 2017 (in response to natural disasters) in the absence of diverse firms' attenuation of shocks. This suggests that supply base diversity, in addition to minimizing output fluctuations at the microeconomic level, also substantially attenuates aggregate volatility.

4 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 whose input purchases are spread across many i) suppliers, ii) geographies, or iii) producers within an industry experience reductions in sales growth $\approx 60-70\%$ smaller than non-diversified firms when at least one supplier is struck with a natural disaster. We then quantify the aggregate effects of supply base diversity using a general equilibrium model of production networks. We find that aggregate volatility would have been $\approx 33\%$ greater between 1978 and 2017 in the absence of shock mitigation by diversified firms.

We show empirically that diverse firms attenuate shocks by temporarily substituting towards unaffected suppliers producing similar inputs, preventing a large drop in their production. However, it remains an open question as to why some firms choose to multi-source inputs while others

[41] In the counterfactual, diverse firms continue to have the same set of suppliers as in the actual economy. The only difference is that diverse firms' elasticity is assumed to be equal to one. This implies that in response to capital-augmenting natural disaster shocks, there is no change in the production network due to substitution by diverse firms, as is the case in the actual economy.

do not. Firms' diversity (or lack thereof) may be explained by idiosyncratic factors such as managers' industry connections or risk aversion. While important, we leave this question for future work.

References

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "Microeconomic Origins of Macroeconomic Tail Risks," *American Economic Review*, January 2017, *107* (1), 54–108.

_, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "The Network Origins of Aggregate Fluctuations," *Econometrica*, 2012, *80* (5), 1977–2016.

Ahern, Kenneth R., "Bargaining power and industry dependence in mergers," *Journal of Financial Economics*, 2012, *103* (3), 530–550.

Altinoglu, Levent, "The Origins of Aggregate Fluctuations in a Credit Network Economy," *Journal of Monetary Economics*, 2021, *117*, 316–334.

Antrás, Pol, Teresa C. Fort, and Felix Tintelnot, "The Margins of Global Sourcing: Theory and Evidence from US Firms," *American Economic Review*, September 2017, *107* (9), 2514–64.

Atalay, Enghin, "How Important Are Sectoral Shocks?," *American Economic Journal: Macroeconomics*, 2017, *9* (4), 254–80.

_, Ali Hortacsu, James Roberts, and Chad Syverson, "Network Structure of Production," *Proceedings of the National Academy of Sciences*, 2011, *108* (13), 5199–5202.

Baldwin, Richard and Rebecca Freeman, "Risks and Global Supply Chains: What We Know and What We Need to Know," *Annual Review of Economics*, 2022, *14* (1), 153–180.

Baqaee, David Rezza, "Cascading Failures in Production Networks," *Econometrica*, 2018, *86* (5), 1819–1838.

— and Emmanuel Farhi, "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hultenâs Theorem," *Econometrica*, 2019, *87* (4), 1155–1203.

— and —, "Productivity and Misallocation in General Equilibrium," *The Quarterly Journal of Economics*, 09 2020, *135* (1), 105–163.

Barrot, Jean-Noël and Julien Sauvagnat, "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *The Quarterly Journal of Economics*, 2016, *131* (3), 1543–1592.

Bartelme, Dominick and Yuriy Gorodnichenko, "Linkages and Economic Development," Working Paper 21251, National Bureau of Economic Research June 2015.

Bernard, Andrew B., Andreas Moxnes, and Yukiko U. Saito, "Production Networks, Geography, and Firm Performance," *Journal of Political Economy*, 2019, *127* (2), 639–688.

Bigio, Saki and Jennifer La'O, "Distortions in Production Networks," *The Quarterly Journal of Economics*, 05 2020, *135* (4), 2187–2253.

Boehm, Christoph E., Aaron Flaaen, and Nitya Pandalai-Nayar, "Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tōhoku Earthquake," *The Review of Economics and Statistics*, 2019, *101* (1), 60–75.

Boehm, Johannes, "The Impact of Contract Enforcement Costs on Value Chains and Aggregate Productivity," *The Review of Economics and Statistics*, 06 2020, pp. 1–45.

— and Ezra Oberfield, "Misallocation in the Market for Inputs: Enforcement and the Organization of Production*," *The Quarterly Journal of Economics*, 06 2020, *135* (4), 2007–2058.

Caliendo, Lorenzo, Fernando Parro, and Aleh Tsyvinski, "Distortions and the Structure of the World Economy," *American Economic Journal: Macroeconomics*, forthcoming.

— , — , **Esteban Rossi-Hansberg, and Pierre-Daniel Sarte**, "The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy," *The Review of Economic Studies*, 12 2017, *85* (4), 2042–2096.

Carvalho, Vasco M., "From Micro to Macro via Production Networks," *Journal of Economic Perspectives*, November 2014, *28* (4), 23–48.

— **and Alireza Tahbaz-Salehi**, "Production Networks: A Primer," *Annual Review of Economics*, 2019, *11* (1), 635–663.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi, "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," *The Quarterly Journal of Economics*, 12 2021, *136* (2), 1255–1321.

Carvalho, Vasco, Matthew Elliott, and John Spray, "Network Bottlenecks and Market Power," Working Paper 2022.

Choi, Thomas Y and Daniel R Krause, "The Supply Base and Its Complexity: Implications for Transaction Costs, Risks, Responsiveness, and Innovation," *Journal of Operations Management*, 2006, *24* (5), 637–652.

Chu, Yongqiang, Xuan Tian, and Wenyu Wang, "Corporate Innovation Along the Supply Chain," *Management Science*, 2019, *65* (6), 2445–2466.

Durlauf, Steven N., "Nonergodic Economic Growth," *The Review of Economic Studies*, 04 1993, *60* (2), 349–366.

Elliott, Matthew, Benjamin Golub, and Matthew V. Leduc, "Supply Network Formation and Fragility," *American Economic Review*, August 2022, *112* (8), 2701–47.

Farrell, Henry and Abraham L. Newman, "Weak links in finance and supply chains are easily weaponized," *Nature*, 2022, *605*, 219–22.

Fee, C Edward, Charles J Hadlock, and Shawn Thomas, "Corporate Equity Ownership and the Governance of Product Market Relationships," *The Journal of Finance*, 2006, *61* (3), 1217–1251.

Financial Accounting Standards Board, "Statement of Financial Accounting Standards No. 131," Technical Report 131, Financial Accounting Foundation 1997.

Fortune, "94% Of the Fortune 1000 Are Seeing Coronavirus Supply Chain Disruptions: Report," 2020.

Grassi, Basile, "IO in I-O: Competition and Volatility in Input-Output Networks," *Meeting Papers 1637*, 2017.

Hendricks, Kevin B., Vinod R. Singhal, and Rongrong Zhang, "The Effect of Operational Slack, Diversification, and Vertical Relatedness on the Stock Market Reaction to Supply Chain Disruptions," *Journal of Operations Management*, 2009, *27* (3), 233 – 246.

Horvath, Michael, "Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks," *Review of Economic Dynamics*, 1998, *1* (4), 781–808.

_ , "Sectoral Shocks and Aggregate Fluctuations," *Journal of Monetary Economics*, 2000, *45* (1), 69–106.

Hsu, Po-Hsuan, Hsiao-Hui Lee, Shu-Cing Peng, and Long Yi, "Natural Disasters, Technology Diversity, and Operating Performance," *Review of Economics and Statistics*, 2018, *100* (4), 619–630.

Hulten, Charles R, "Growth Accounting With Intermediate Inputs," *The Review of Economic Studies*, 1978, *45* (3), 511–518.

Inoue, Hiroyasu and Yasuyuki Todo, "Propagation of Negative Shocks Through Firm Networks: Evidence From Simulation on Comprehensive Supply-Chain Data," *RIETI, Discusson Paper*, 2017.

— **and** — , "Firm-Level Propagation of Shocks Through Supply-Chain Networks," *Nature Sustainability*, 2019, *2* (9), 841–847.

Jones, Charles I., "Intermediate Goods and Weak Links in the Theory of Economic Development," *American Economic Journal: Macroeconomics*, April 2011, *3* (2), 1–28.

— , *Misallocation, Economic Growth, and Input-Output Economics*, Vol. 2 of *Econometric Society Monographs*, Cambridge University Press,

Jovanovic, Boyan, "Micro Shocks and Aggregate Risk*," *The Quarterly Journal of Economics*, 05 1987, *102* (2), 395–409.

Kinnan, Cynthia, Krislert Samphantharak, Robert Townsend, and Diego Vera-Cossio, "Propagation and Insurance in Village Networks," *American Economic Review*, January 2024, *114* (1), 252–84.

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Long, John B and Charles I Plosser, "Real Business Cycles," *Journal of political Economy*, 1983, *91* (1), 39–69.

Nishiguchi, Toshihiro and Alexandre Beaudet, "The Toyota Group and the Aisin Fire," *Sloan management review*, 1998, *40* (1), 49.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," *Econometrica*, 2021, *89* (2), 703–732.

Peter, Alessandra and Cian Ruane, "The Aggregate Importance of Intermediate Input Substitutability," Working Paper 2020.

Peters, Ryan H. and Lucian A. Taylor, "Intangible Capital and the Investment-q Relation," *Journal of Financial Economics*, 2017, *123* (2), 251–272.

Rauch, James E., "Networks Versus Markets in International Trade," *Journal of International Economics*, 1999, *48* (1), 7–35.

Ro, Christine, "The Material That Powered Pandemic Life," 2020.

The New York Times, "Stacked Up At Boeing; Plane Giant Tries to Recover From Its Snarls in Production," 1997.

Vincenty, Thaddeus, "Direct and Inverse Solutions of Geodesics on the Ellipsoid With Application of Nested Equations," *Survey Review*, 1975, *23* (176), 88–93.

ONLINE APPENDIX

A Supplementary Figures and Tables

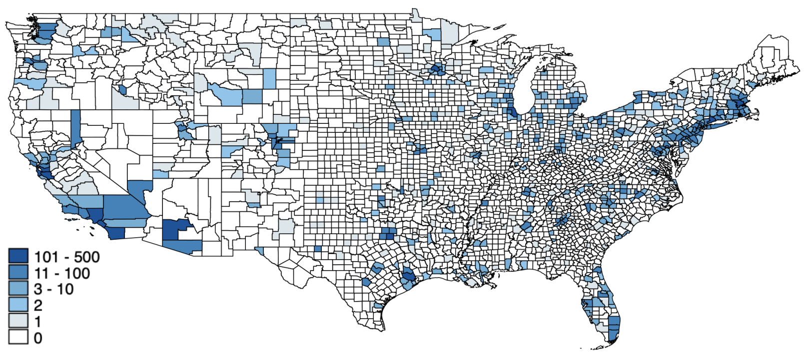

Figure A.1: Distribution of Firm Headquarters by US County (1978-2017)

Note: This figure depicts the distribution of firm headquarters across our sample of US firms between 1978 and 2017 at the county level. Shading represents the number of distinct firms reporting a given county as its headquarters location in at least one quarter. Firms' locations are taken from Compustat and are adjusted to reflect historical changes in the location of headquarters.

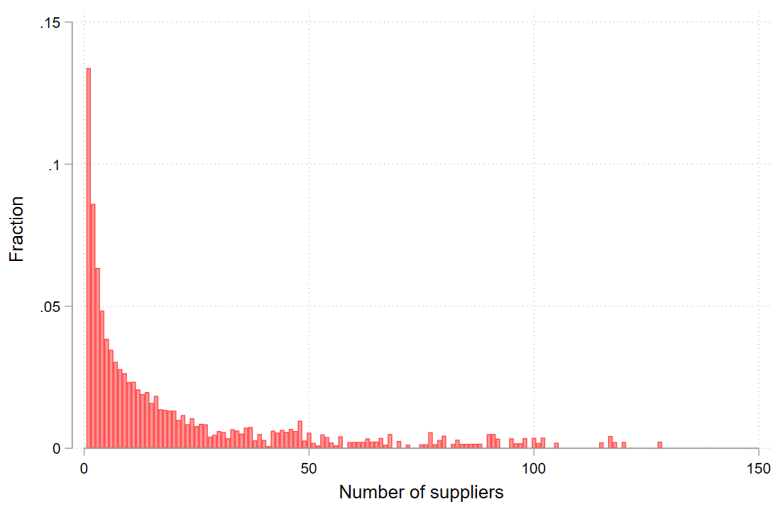

Figure A.2: Distribution of Firms' Number of Suppliers

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

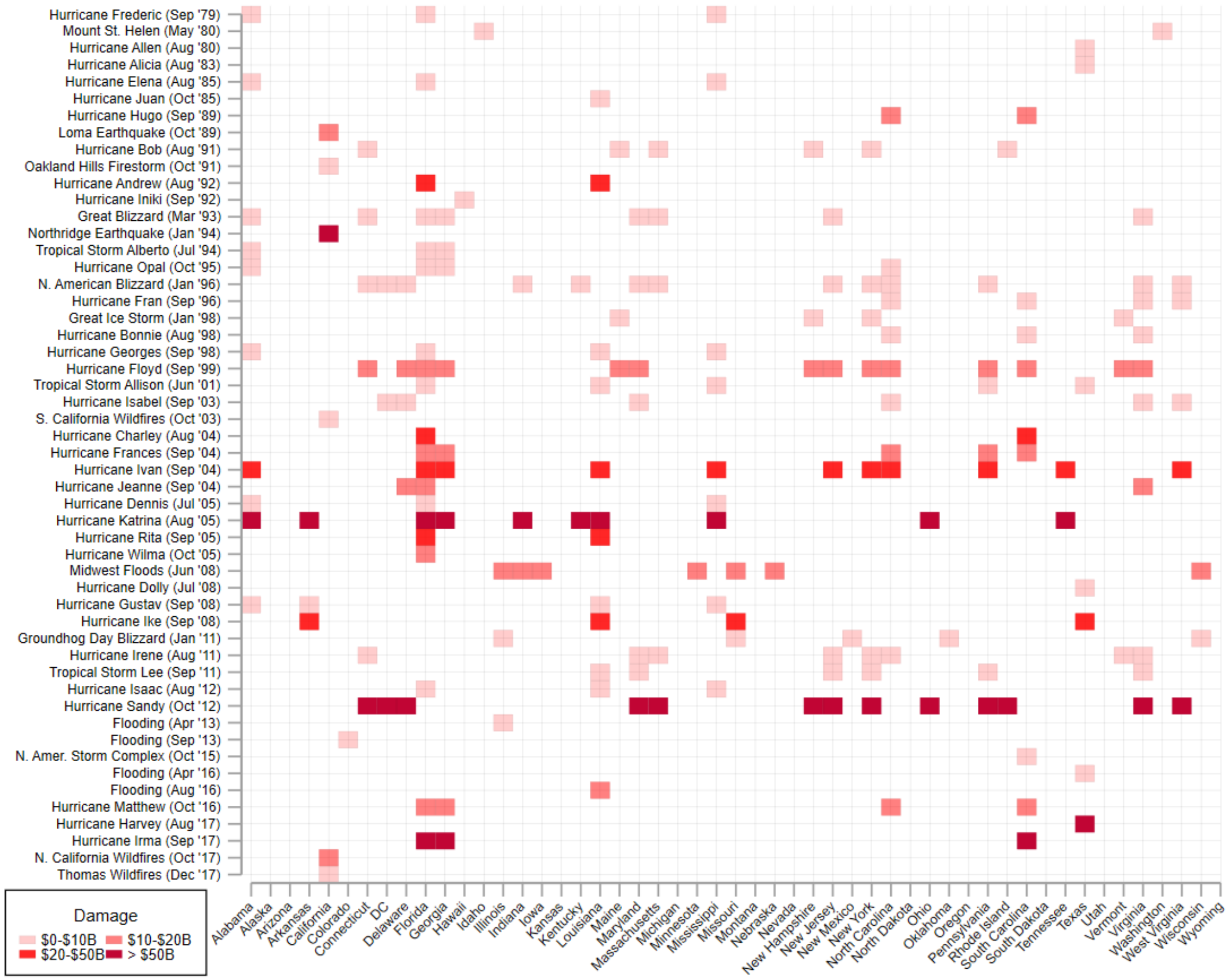

Figure A.3: Major Natural Disasters by US States (1978-2017)

Note: The figure shows all major natural disasters in the US between January 1978 and December 2017, the states affected, and the total damage caused by each disaster (across all states) in 2017 US dollars.

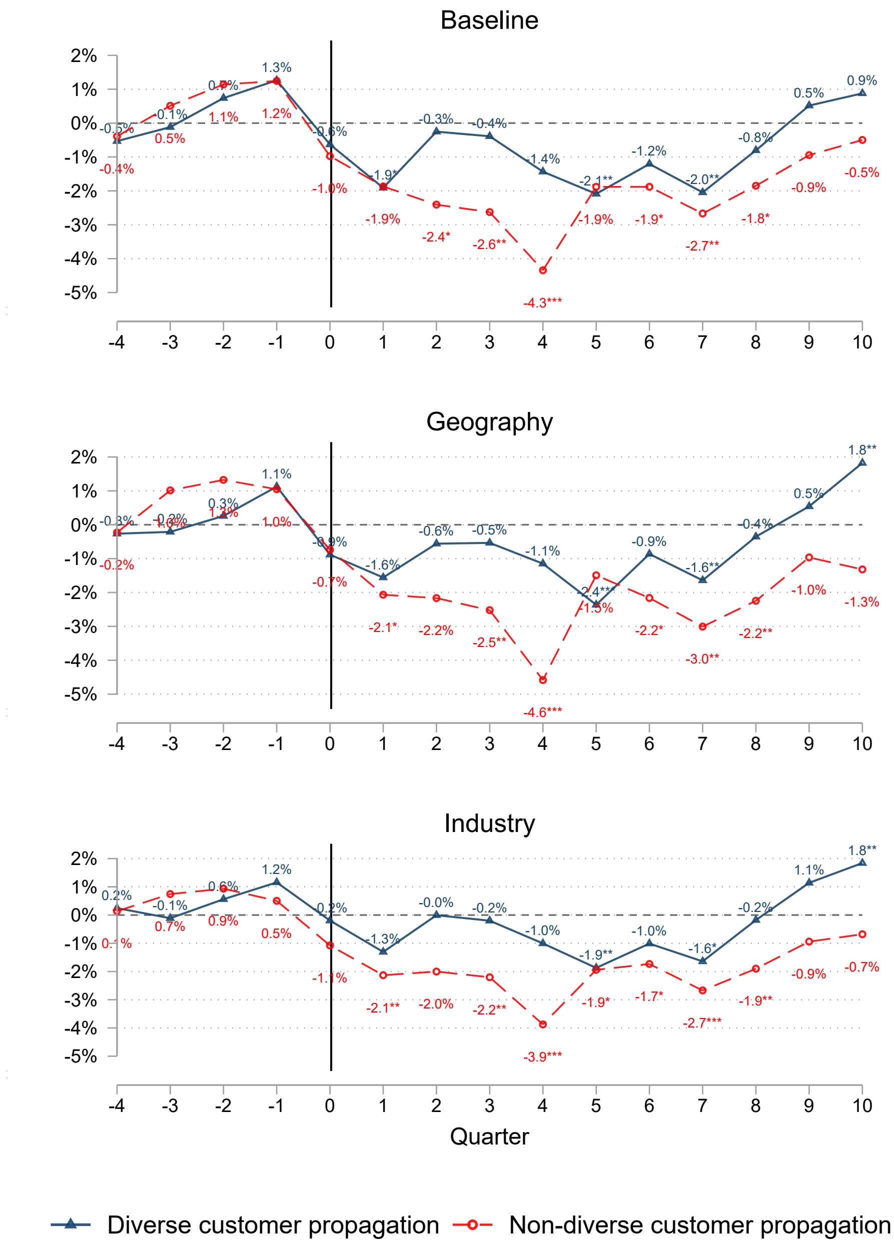

Figure A.4: Parallel Trends

Note: This figure shows the average propagation effect of natural disasters on non-diverse firms' sales growth (red dashed line) as well as diverse firms' sales growth (solid blue line). All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, control variables for firms' number of suppliers, number of employees and age, and dummy variables for the tercile of firm size, and ROA interacted with year-quarter indicators. Standard errors are clustered at the firm level. *10%; **5%; ***1% significance levels.

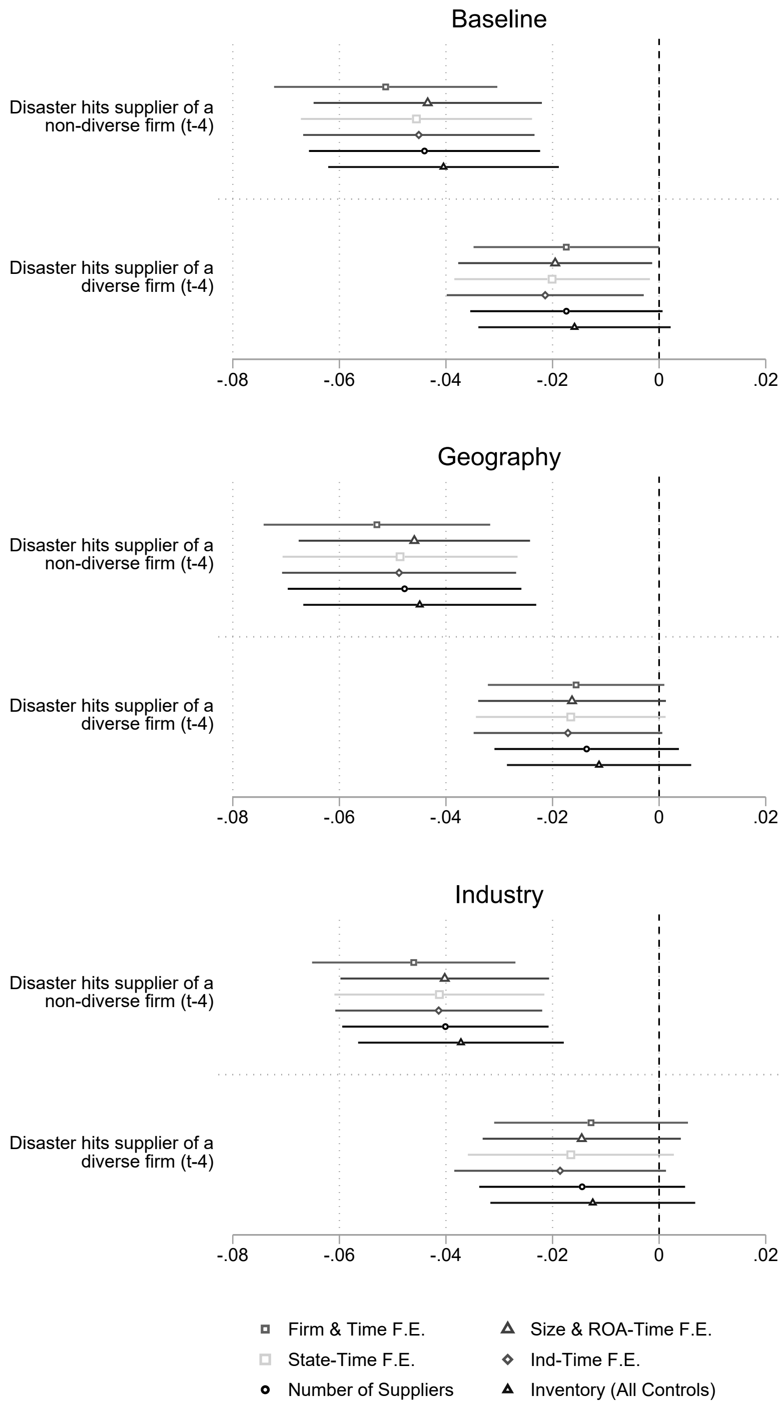

Figure A.5: The Effect of Supply Base Diversity on Shock Propagation (Robustness)

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. The final specification includes a tercile dummy of firms' inventory-to-sales ratio.

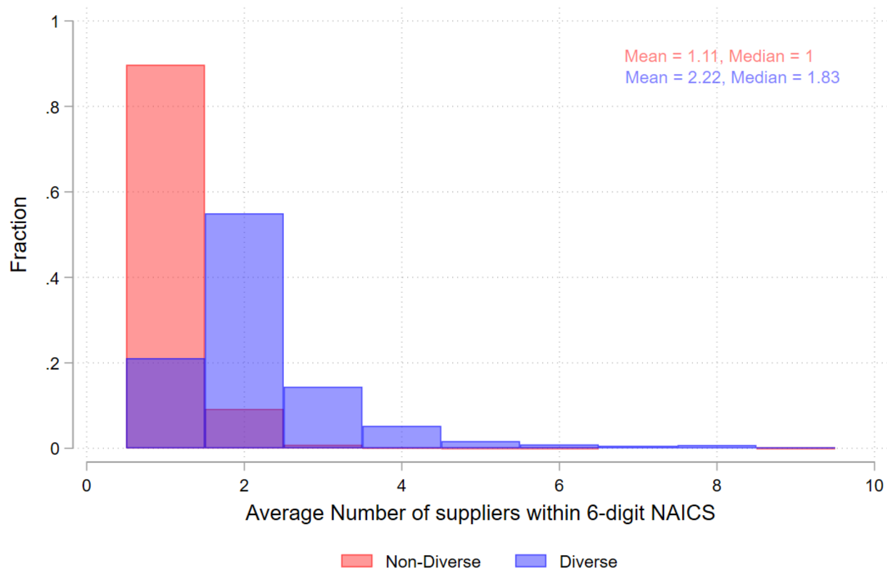

Figure A.6: Distribution of Firms' Number of Suppliers Within 6-digit NAICS Industries

Note: This figure shows the distribution of suppliers within 6-digit NAICS industries for diverse and non-diverse firms (as measured by $\mathcal{I}_{i,t}$). For visibility, we show the distributions up to ten suppliers (on the horizontal axis), which covers more than 99 percent of each distribution.

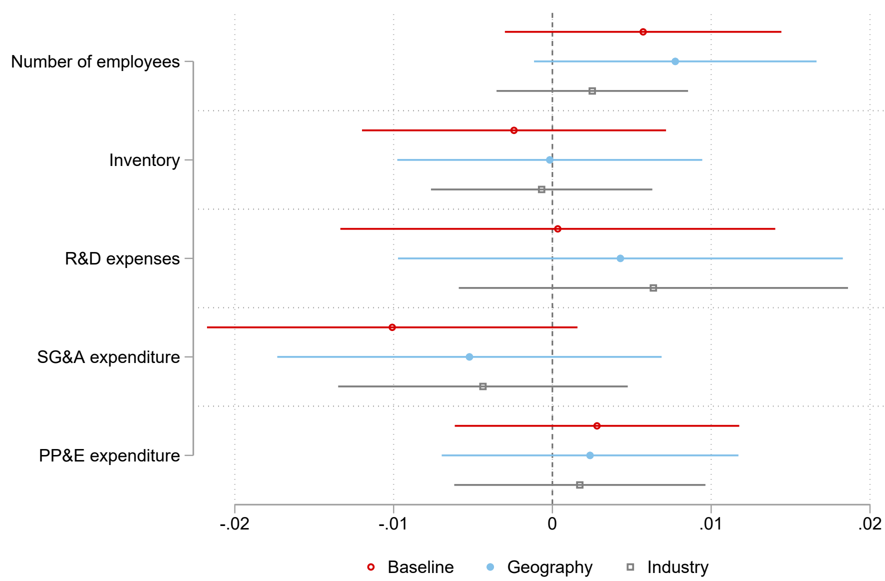

Figure A.7: Orthogonality of Diversity Measures with Other Firm Attributes

Note: This figure presents results from regressions of each diversity indicator on the firm attribute listed on the vertical axis and all other controls included in Table 2. *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 A.1: Do Shocks Propagate When Links Are Not Active?

	(1)	(2)	(3)	(4)
Disaster hits eventually linked supplier $(t-4)$	0.007	0.004	0.005	0.005
	[0.007]	[0.007]	[0.007]	[0.007]
Disaster hits one supplier $(t-4)$	-0.044***	-0.038***	-0.033***	-0.032***
	[0.008]	[0.008]	[0.008]	[0.008]
Disaster hits firm $(t-4)$	-0.022**	-0.016	-0.020**	-0.020**
	[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
Age & number of employees controls	No	No	No	Yes
Number of suppliers	No	No	No	Yes
Observations	95,455	95,455	95,455	95,455
Adjusted R^2	0.165	0.201	0.219	0.220

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. The regressions progressively include the controls discussed in Section 3. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.2: Downstream Propagation with Random Customer Diversity

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.009	0.010	-0.013	-0.013	-0.025	-0.016
	[0.021]	[0.021]	[0.018]	[0.019]	[0.023]	[0.022]
Disaster hits one supplier $(t-4)$	-0.034***	-0.032***	-0.031***	-0.029***	-0.031***	-0.029***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.007]	[0.008]
Disaster hits firm $(t-4)$	-0.016	-0.020**	-0.016	-0.020**	-0.016	-0.020**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	0.001	0.002	-0.002	-0.003	-0.001	-0.000
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Age & number of employees controls	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	95,455	95,455	95,455	95,455	95,455	95,455
Adjusted R^2	0.202	0.220	0.202	0.220	0.202	0.220

Notes: This table presents estimates for regression (3) but where customer firms are randomly classified as diverse. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset and the same set of controls as in Table 2. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.3: 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 $(t-4)$	0.062***	0.045**	0.076***	0.058***	0.106***	0.079***
	[0.018]	[0.018]	[0.021]	[0.021]	[0.031]	[0.030]
Disaster hits one supplier $(t-4)$	-0.051***	-0.044***	-0.052***	-0.045***	-0.043***	-0.038***
	[0.011]	[0.011]	[0.010]	[0.011]	[0.009]	[0.009]
Disaster hits firm $(t-4)$	-0.016	-0.020**	-0.016	-0.020**	-0.016	-0.020**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.028	-0.009	-0.019	-0.002	-0.024	-0.008
	[0.019]	[0.017]	[0.022]	[0.019]	[0.033]	[0.031]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA × year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	95,455	95,455	95,455	95,455	95,455	95,455
Adjusted R^2	0.202	0.220	0.202	0.220	0.202	0.220

Notes: This table presents estimates for specification (3), but with continuous Herfindahls instead of tercile dummies to measure firms' diversity. Since diverse firms record a value closer to zero in the original Herfindahls, we measure diversity as one minus the indexes $\mathcal{H}, \mathcal{G}$, and $\mathcal{I}$. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.4: Customer Diversity and Bargaining Power

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster hits one of diverse firm's suppliers $(t-4)$	0.056***	0.043**	0.070***	0.056***	0.096***	0.075**
	[0.020]	[0.020]	[0.022]	[0.022]	[0.031]	[0.030]
Bargaining power × Disaster hits one supplier $(t-4)$	0.033	0.022	0.033	0.021	0.051	0.035
	[0.040]	[0.040]	[0.039]	[0.039]	[0.038]	[0.038]
Disaster hits one supplier $(t-4)$	-0.055***	-0.047***	-0.056***	-0.048***	-0.051***	-0.044***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.011]	[0.011]
Disaster hits firm $(t-4)$	-0.016	-0.020**	-0.016	-0.020**	-0.016	-0.020**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Diverse firm	-0.027	-0.012	-0.018	-0.005	-0.023	-0.010
	[0.018]	[0.017]	[0.022]	[0.019]	[0.032]	[0.031]
Bargaining power	-0.003	0.020	-0.005	0.019	-0.007	0.018
	[0.021]	[0.021]	[0.021]	[0.020]	[0.021]	[0.020]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of suppliers control	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA × year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	95,455	95,455	95,455	95,455	95,455	95,455
Adjusted R^2	0.202	0.220	0.202	0.220	0.202	0.220

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. Each regression also includes a measure of firms' *bargaining power*, based on Ahern (2012), and an interaction of *bargaining power* and *Disaster hits one supplier* $(t-4)$. 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 regressions include the same set of controls as in Table 2. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.5: Independence of Supply Base Diversity and Disasters (Intensive Margin)

Diversity type	Baseline		Geography		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of supplier disruptions in the past five years	0.002	0.003	0.001	0.001	0.000	0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]
Number of disasters in the past five years	-0.002	-0.002	-0.000	-0.000	0.001	0.001
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]
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
Age & number of employees controls	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	95,455	95,455	95,455	95,455	95,455	95,455
Adjusted R^2	0.680	0.683	0.645	0.647	0.495	0.497

Notes: This table presents estimates for the regressions of the Baseline, Geography, and Industry diversity Herfindahls ($HHI_{i,t}^{\mathcal{D}}$) on i) the number of supplier disruptions firm i experienced in the past five years and ii) the number of disasters directly experienced by firm i in the previous five years. All other controls, the table format, and the data sample are the same as in Table 2. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.6: 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	0.016**	-0.002
	[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	0.721	0.002	0.694

Notes: This table reports estimates for specifications (5) (columns 1 and 2) and (6) (columns 3 and 4). The unit of observation is a county-year. Natural disaster data are from *EM-DAT* and *OpenFEMA Disaster Declarations* datasets. Data on interfirm linkages is from Computstat's *Customer Segments* dataset.
* p<0.1; ** p<0.05; *** p<0.01.

Table A.7: The 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 $(t-1, t-4)$	0.003	-0.002	-0.001	-0.008	0.019	0.014
	[0.023]	[0.023]	[0.023]	[0.023]	[0.022]	[0.021]
Natural disaster hits firm $(t-1, t-4)$	-0.045**	-0.041**	-0.043**	-0.039*	-0.052***	-0.049***
	[0.021]	[0.021]	[0.020]	[0.020]	[0.019]	[0.019]
Diverse customer control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes	No	Yes
Observations	175,685	175,685	175,685	175,685	175,685	175,685
Adjusted R^2	0.130	0.138	0.130	0.138	0.130	0.138

Notes: This table shows results for regression (1) 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 one if supplier i has at least one customer identified as diverse (according to our baseline, geography, and industry measures) anytime between $(t-1)$ to $(t-4)$. *Disaster hits firm with a diverse customer* $(t-1, t-4)$ is the interaction of a dummy that takes a value one if the supplier firm is struck by a disaster anytime between $(t-1)$ to $(t-4)$ and the *Diverse customer* indicator. All other controls and the data sample are the same as in Figure 3. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.8: 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 $(t-4)$	0.041***	0.032**	0.045***	0.036***	0.041***	0.033**
	[0.014]	[0.014]	[0.013]	[0.014]	[0.013]	[0.013]
Disaster hits specific supplier $(t-4)$	-0.031**	-0.032**	-0.031**	-0.032**	-0.031**	-0.032***
	[0.013]	[0.012]	[0.013]	[0.012]	[0.013]	[0.012]
Disaster hits one supplier $(t-4)$	-0.046***	-0.040***	-0.048***	-0.043***	-0.039***	-0.036***
	[0.011]	[0.011]	[0.011]	[0.012]	[0.010]	[0.010]
Disaster hits firm $(t-4)$	-0.019*	-0.023**	-0.019*	-0.023**	-0.019*	-0.024**
	[0.011]	[0.010]	[0.011]	[0.010]	[0.011]	[0.010]
Diverse firm	-0.013	-0.003	-0.017*	-0.007	-0.028***	-0.017*
	[0.009]	[0.008]	[0.009]	[0.008]	[0.011]	[0.010]
Specific supplier (Patent)	-0.014*	-0.006	-0.014*	-0.006	-0.014*	-0.006
	[0.008]	[0.007]	[0.008]	[0.007]	[0.008]	[0.007]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Age & number of employees controls	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	86,093	86,093	86,093	86,093	86,093	86,093
Adjusted R^2	0.202	0.220	0.202	0.220	0.202	0.220

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 *specific supplier* dummy and *disaster hits supplier*. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset and the same set of controls as in Table 2. Standard errors, represented in square brackets, are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

B Theoretical Appendix

Our empirical findings reveal that supply base diversity has a significant impact on shock propagation at the firm level. Here, we build a general equilibrium model of production networks in the spirit of Acemoglu et al. (2012) and Baqaee and Farhi (2019). The model allows us to measure the aggregate effects of the behavior of diverse firms in minimizing production losses by substituting inputs from affected to unaffected suppliers.

In our model, the substitution behavior of diverse firms attenuates the impact of natural disasters on *aggregate* output. To estimate the macroeconomic effect of diversity, we compare the model-implied level of GDP volatility with a counterfactual where diverse firms do not substitute (and thus act like non-diverse firms). Our counterfactual analysis reveals that supply base diversity substantially attenuates the effects of adverse shocks at the macroeconomic level.

B.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 $\mathcal{S}$ is also the union of $\mathcal{D}$ and $\mathcal{N}$, $\mathcal{D} \cup \mathcal{N}$. 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. There are no firms that (at a particular point in time) are simultaneously classified as diverse and non-diverse. 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:

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

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 ω_{ij} 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 an elasticity of substitution $\theta_{\mathcal{D}}$. In other words, diverse and non-diverse firms have different abilities to substitute across their set of suppliers in response to upstream shocks (as shown empirically in Figure 4).

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

$$y_i = c_i + \sum_{j \in \mathcal{D}} x_{ji} + \sum_{j \in \mathcal{N}} x_{ji}. \tag{B.1}$$

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 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.

B.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 diverse firm i's expenditure on j, as a share of i's revenues:

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

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 firms.

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

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

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

Finally, the *full* 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.[42]

[42] 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.

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

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

The ij^{th} element of the Leontief inverse $\boldsymbol{\Psi}$ records all direct and indirect ways through which firm $i \in \mathcal{S}$ uses inputs from $j \in \mathcal{S}$. In particular, $(\boldsymbol{\Omega}^n)_{ij}$ 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:

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

As with the diverse input-output matrix $\boldsymbol{\Omega}_{\mathcal{D}}$, 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 firms is defined as $\boldsymbol{\lambda} = \boldsymbol{\lambda}_{\mathcal{D}} + \boldsymbol{\lambda}_{\mathcal{N}}$. Intuitively, Domar weights capture all direct and indirect exposures from a given firm to final demand.

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 on capital, as a fraction of 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 goods. As we will see in Section B.7, capital expenditure shares (and changes in capital shares) are sufficient statistics for characterizing the impact of natural disasters on real GDP.

B.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 parameters by linear regression. Aligning with the results of Section B.4, we streamline the discussion of our theoretical results by restricting diverse firms' elasticity of substitution to be greater than one $\theta_{\mathcal{D}} > 1$, implying gross substitutability between suppliers for these firms. In contrast, we impose $\theta_{\mathcal{N}} \leq 1$, meaning non-diverse firms cannot shift expenditures towards unaffected suppliers in response to shocks.[43]

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

$$\frac{d \log \lambda_i}{d \log z_j} = \underbrace{(\theta_{\mathcal{D}} - 1) \frac{\eta_j}{\lambda_i \lambda_j} \sum_{k \in \mathcal{D}} \sum_{m \in S} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right)}_{\textit{Demand effect of diverse firms}} + \underbrace{(\theta_{\mathcal{N}} - 1) \frac{\eta_j}{\lambda_i \lambda_j} \sum_{k \in \mathcal{N}} \sum_{m \in S} \Omega_{km} \lambda_k \Psi_{mi} \left(\Psi_{mj} - \Psi_{kj} \right)}_{\textit{Demand effect of non-diverse firms}}. \quad \text{(B.2)}$$

Proof. See Appendix C.

Proposition 1 highlights the role of the economy's production network in the propagation of natural disaster shocks. We first discuss how a shock to firm j affects the sales share (Domar weight) of

[43] In Section B.4, we estimate $\theta_{\mathcal{D}}$ to be between 3.21 and 3.58, whereas $\theta_{\mathcal{N}}$ is approximately 1.

firm i due to substitution by the diverse firms in the economy, $k \in \mathcal{D}$ (the first term in Equation B.2). The key intuition of the first term is 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 term $(\Psi_{mj} - \Psi_{kj})$ shows that the extent of substitution depends on the difference between k's and m's overall reliance on the disrupted firm j.[44] In other words, the diverse firm substitutes expenditure towards those suppliers that are relatively less exposed to the shock.[45] Naturally, the extent of substitution increases with i) k's expenditure on m's output as a proportion of k's total input expenditure (Ω_{km}), ii) m's direct and indirect reliance on i (Ψ_{mi}), iii) j's sensitivity to natural disasters (i.e., j's expenditure on capital as a fraction of its sales, η_j/λ_j), and iv) the size of diverse firm k relative to i (λ_k/λ_i).[46] Overall, i's Domar weight changes because diverse firms substitute away from shocked suppliers to firms that are relatively less affected directly or indirectly, which ultimately changes the demand for i's product in equilibrium.

The second term in Equation (B.2) describes how the behavior of non-diverse firms influences i's Domar weight. When $\theta_{\mathcal{N}} = 1$ (i.e., production technologies of non-diverse firms are Cobb-Douglas), there is no change in the relative expenditure on inputs from shocked suppliers. Hence, there is no resulting demand effect on firm i due to non-diverse firms. When $\theta_{\mathcal{N}} < 1$, non-diverse firms spend more on inputs from firms that are relatively more exposed to the shock ($\Psi_{mj} > \Psi_{kj}$). This is because, in the absence of multi-sourcing similar intermediate goods, non-diverse firms increase expenditure on disrupted inputs whose prices increase as a result of the shock. As before, the demand effect of non-diverse firms increases with m's expenditure on k as a share of k's total input costs (Ω_{km}), the size of non-diverse firm k relative to i (λ_k/λ_i), and j's sensitivity to disasters (or its capital intensity, η_j/λ_j).[47]

[44] 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 all $\{\Omega_{km}\}_{m \in \mathcal{S}}$ are necessarily equal to zero.

[45] That is, if $\Psi_{mj} < \Psi_{kj}$ and $\theta_{\mathcal{D}} > 1$, then a negative shock to j will increase k's demand for m's product.

[46] Changes in relative prices induce diverse firms to substitute across suppliers. 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 firm m is to the shock, the greater the increase in its price.

[47] 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.

The macroeconomic impact of natural disasters. Our main objective is to use our model to measure the macroeconomic impact of supply base diversification. To do this, we must first characterize how natural disaster shocks affect real GDP by propagating through the network, affecting final demand. To a first-order approximation, the effect of a firm-level capital-augmenting shock on aggregate output is sufficiently summarized by the shocked firm's capital expenditure share.[48]

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 a second-order 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 impact of diversity, we 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 (which rest upon the values of $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$) are sufficient to summarize how shocks affect GDP to a second-order approximation.

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

$$\frac{d^2 \log Y}{d\log z_j d\log z_i} = \frac{d\eta_i}{d\log z_j} = (1-\theta_s)\eta_i \left[\Psi_{ij}\frac{\eta_j}{\lambda_j} - \mathbf{1}(i=j)\right] + \eta_i \frac{d\log \lambda_i}{d\log z_j}, \tag{B.3}$$

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 C.

To understand the intuition behind Equation (B.3), consider the economy shown in Figure B.1. 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 (B.2). Furthermore, assume firm i is diverse with elasticity of substitution $\theta_{\mathcal{D}} > 1$. The negative shock to j causes i to

[48] We show this result in the Proof of Proposition 2 below.

reduce expenditure on j while increasing its spending on capital and intermediates from its 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. For more general production structures

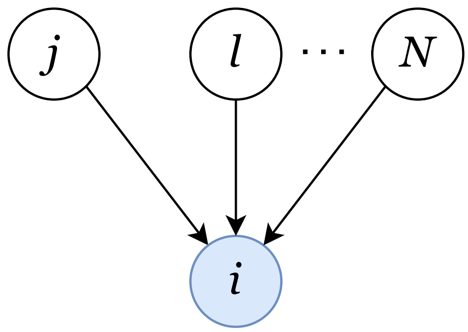

Figure B.1: Example Network

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.

than the economy shown in Figure B.1, the term $\frac{d \log \lambda_i}{d \log z_j}$ is (in general) non-zero. As discussed above, the change in firm i's sales share depends crucially on the substitution behavior by all diverse and non-diverse firms and the relative exposure of each set of firms to the shocks.

B.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.

We first outline how we estimate the elasticities presented in Table B.1. First, note that Equation (B.2) expresses the change in any given firm's sales share as a function of the elasticities of substitution and production network parameters. Therefore, using the EM-DAT and *OpenFema* natural disaster data in conjunction with the Compustat data on supplier-customer relationships, Equation (B.2) provides us with a natural starting point for estimating the model. In response to a vector of shocks $\Delta \log \mathbf{z}$, Equation (B.2) can be written in matrix form to characterize firms' sales shares,

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

where $\boldsymbol{\lambda}^{post}$ is an $N \times 1$ vector of post-shock Domar weights 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 B.2, all of which are measured at the initial (pre-shock) equilibrium. 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 C for an exact definition of $\mathbf{M}$), *Diverse* and *Non-diverse* are $N \times 1$ vectors of input-output parameters, and $\circ$ denotes the Hadamard product.

The above equation is jointly linear in $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$, permitting the estimation of the model by linear regression as in Carvalho et al. (2021).

This means we can estimate the elasticities of substitution $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ via the following specification:

$$\log \lambda_{it}^{post} = \alpha + \beta_1 \cdot Diverse_{i,t-4} + \beta_2 \cdot Non\text{-}diverse_{i,t-4} + \mathbf{X}_{it} + \gamma_i + \tau_t + \varepsilon_{it}, \tag{B.4}$$

where $\theta_{\mathcal{D}} = \beta_1 + 1$, $\theta_{\mathcal{N}} = \beta_2 + 1$ and γ_i and τ_t are firm and year-quarter fixed effects, respectively. To align with our empirical results in Section 3, in some specifications, we also control for fiscal-quarter fixed effects, firm size and return on assets (ROA) interacted with year-quarter fixed effects, and controls for firms' number of employees, age and number of suppliers. Moreover, we include the fourth lag of the covariates *Diverse* and *Non-diverse* in our regressions, meaning our estimated elasticities measure the degree of substitutability over a one-year horizon.

To estimate the average θ across diverse and non-diverse firms, we first build the covariate

$$All\ Firms = \operatorname{diag}(\boldsymbol{\lambda})^{-1} \boldsymbol{\Psi}' \left(\Delta \log \mathbf{z} \circ \mathbf{M} \cdot \boldsymbol{\Omega}' - \boldsymbol{\Omega}' \cdot \Delta \log \mathbf{z} \circ \mathbf{M} \right) \boldsymbol{\lambda}.$$

Then, we run the regression

$$\log \lambda_{it}^{post} = \alpha + \beta_A * All\ Firms_{i,t-4} + \mathbf{X}_{it} + \gamma_i + \tau_t + \varepsilon_{it} \tag{B.5}$$

where $\theta = \beta_A + 1$. Below, we discuss how we build the covariates *Diverse*, *Non-diverse* and *All firms* in Equations (B.4) and (B.5).

B.5 Constructing the covariates

Input-output data and aggregate Data. Our input-output data comes from the BEA's annual "Use" tables from 1978-2017 (before redefinitions).[49] 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.

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

Natural disaster data and county-level data. We construct the shock vector ($\Delta \log \mathbf{z}$) 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).[50] We compute the county-level shock by dividing nominal FIPS-level damages by our estimate of the

[49] "Before redefinitions" refers to the treatment of industries' secondary production. If a given industry produces a secondary product that uses very different inputs from the industry's primary product, the secondary product (output and inputs) is reallocated (redefined) to the industry for which the product is primary. The input-output tables we use do not correct for this.

[50] 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.

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 aggregate damage for a given FIPS-quarter, we sum across all disasters hitting the county in the quarter. We assume all firms in a given county are subject to the same shock. Finally, we deflate the resulting firm-level capital stocks using the GDP deflator (FRED series *GDPDEF*).

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 sector-level input-output data from the BEA. 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.[51]

[51] 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.

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). Since estimates of intangible capital appear at the annual frequency, we linearly interpolate these data to generate quarterly estimates.

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 et al. (2020),

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

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 et al. (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 (`https://pages.stern.nyu.edu/~adamodar/`). The rate of depreciation is 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. That is, the investment price index divided by the PCE deflator (FRED series *PIRIC*).

B.6 Estimates of $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$

Table B.1 reports estimates for the elasticities of substitution $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$ implied by regression (B.4) over a one-year horizon.[52] We also compute the average elasticity θ across all firms in our sample. In our preferred specification with all controls (column 3), we estimate a value of $\theta_{\mathcal{D}}$ = 3.206 (std. err. = 0.791), suggesting a high degree of substitutability between inputs for diverse firms.

Table B.1: Estimates of Elasticities of Substitution

	Diverse & Non-Diverse			Average
	(1)	(2)	(3)	(4)
$\theta_{\mathcal{D}}$ (Diverse)	3.581***	3.261***	3.206***	
	[0.810]	[0.788]	[0.791]	
$\theta_{\mathcal{N}}$ (Non-diverse)	0.981	1.068	1.069	
	[0.311]	[0.282]	[0.285]	
θ (All Firms)				1.139***
				[0.046]
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	Yes	Yes
Number of suppliers control	No	No	Yes	Yes
Age & number of employees controls	No	No	Yes	Yes
Observations	148,219	148,219	148,219	148,219
Adjusted R^2	0.748	0.762	0.767	0.767

Notes: This table reports estimates for regression specification (B.4). The dependent variable in all regressions is the log of firms' Domar weight. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm and year-quarter fixed effects. Column (2) adds dummy variables for the tercile of firm size, and ROA interacted with year-quarter fixed effects, and columns (3) and (4) include control variables for firms' number of suppliers, number of employees, and age. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

For non-diverse firms, across all specifications, our estimates for $\theta_{\mathcal{N}}$ are not statistically different from one, meaning we cannot reject the hypothesis that production functions are Cobb-Douglas for non-diverse firms. Finally, we estimate the average elasticity across all firms in the sample θ,

[52] The number of observations shown in Table B.1 differs from that of Table 2 because we include all supplier *and* customer firm-quarters between 1978 and 2017, as opposed to only customer-quarters as in Table 2.

irrespective of whether they are diverse or non-diverse. As shown in column (4), we estimate $\theta = 1.139$, which is significant at the 1% level, implying that inputs are weakly substitutable on average.

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. 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. Over shorter time horizons (five years), Peter 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 an average firm-level elasticity of 1.18, which is very close to our estimate in column (4) of Table B.1. The estimates of Carvalho et al. (2021) are larger than those of Boehm et al. (2019), 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.

B.7 Estimating the macroeconomic effect 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 effect 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 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 (η_i's) are dependent on $\theta_{\mathcal{D}}$ and $\theta_{\mathcal{N}}$. The above expression, therefore, provides us with an avenue for estimating how the behavior of diverse firms influences real GDP. In line with our results in Table B.1, we set $\theta_{\mathcal{N}} = 1$, meaning non-diverse firms do not change their demand expenditure in response to shocks. Furthermore, a value of $\theta_{\mathcal{N}} = 1$ implies that all second-order effects are solely attributable to diverse firms.

Proposition 3 characterizes the macroeconomic effect of supply base diversity by isolating the change in GDP due to substitution by diverse firms.

Proposition 3. *The macroeconomic effect of supply base diversification ($\mathcal{L}$) is*

$$\mathcal{L} = (\theta_{\mathcal{D}} - 1) \cdot \frac{1}{2} \cdot \Delta \log \mathbf{z}' \cdot \text{diag}(\boldsymbol{\eta}) \Delta_{\mathcal{D}} \cdot \Delta \log \mathbf{z}, \tag{B.6}$$

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

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

Proof. See Appendix C.

Equation (B.6) isolates the behavior of diverse firms in the change in real GDP growth when there are disturbances to the economy. The effect of diversity at the macroeconomic level (measured by $\mathcal{L}$) is increasing (*ceteris paribus*) in the elasticity of substitution of diverse firms ($\theta_{\mathcal{D}}$) 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 1 in Appendix C, 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 and, hence, on the specific structure of the economy's production network. Our quantitative results below reveal that supply base diversity has a consequential impact on aggregate output by mitigating the effects of negative supply shocks.

Table B.2: 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 effect of diversity in Table B.3. 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, deflated to 2017 USD.

Results. We estimate the effect of supply base diversity on real GDP volatility by first selecting quarters in which total disaster damages exceeded $50 billion across all US states.[53] Our sample has six such quarters, dating from 1992Q3 to 2017Q3. Table B.2 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.

We then compute the model-implied aggregate volatility, $\sigma_{\mathcal{D}}$, which accounts for the substitution behavior of diverse firms. $\sigma_{\mathcal{D}}$ denotes the standard deviation of real output growth resulting from firm-level supply shocks, measured as

$$\sigma_{\mathcal{D}} = \text{s.d.}\left(\Delta \log Y_q^{1\text{st}} + \mathcal{L}_q\right)$$

. Here, $\Delta \log Y_q^{1\text{st}}$ represents the first-order change in real GDP in quarter q (with q indexing each quarter listed in Table B.2), and $\mathcal{L}_q$ is the macroeconomic effect of diversity expressed as a per-

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

centage change in GDP (as shown in Equation B.5).

In the counterfactual, we assume that diverse firms do not shift expenditures away from affected suppliers and thus behave like non-diverse firms. Counterfactual aggregate volatility, denoted by $\sigma_{\mathcal{C}}$, is measured as the standard deviation of real GDP growth in the absence of diverse firms' substitution from affected to unaffected suppliers in response to shocks. Specifically, $\sigma_{\mathcal{C}} = \text{s.d.}\left(\Delta \log Y_q^{1\text{st}}\right)$. Since $\sigma_{\mathcal{C}}$ excludes $\mathcal{L}_q$ (the macroeconomic effect of diversity), comparing it to aggregate volatility in the full model ($\sigma_{\mathcal{D}}$) provides an estimate of the contribution of diverse firms' substitution behavior to aggregate fluctuations.

Table B.3: The Effect of Supply Base Diversity on Aggregate Volatility

σ_{Actual}	$\sigma_{\mathcal{D}}$	$\sigma_{\mathcal{C}}$	$\frac{\sigma_{\mathcal{C}}-\sigma_{\mathcal{D}}}{\sigma_{\mathcal{D}}}$
0.0202	0.0186	0.0247	32.8%

Notes: This table presents estimates of aggregate volatility with and without the attenuation of shocks by diverse firms. σ_{Actual} is a measure of quarterly year-on-year real GDP volatility between 1978 and 2017, computed using real GDP data from the BEA. $\sigma_{\mathcal{D}}$ is model-implied GDP volatility, inclusive of the attenuation effects of supply base diversity, and $\sigma_{\mathcal{C}}$ is counterfactual GDP volatility, which excludes attenuation by diverse firms. Finally, $\frac{\sigma_{\mathcal{C}}-\sigma_{\mathcal{D}}}{\sigma_{\mathcal{D}}}$ is the aggregate effect of supply base diversity on GDP volatility.

Our quantitative results are shown in Table B.3. To benchmark our estimates, we compare the observed GDP volatility between 1978 and 2017 (σ_{Actual}), computed using data from the Bureau of Economic Analysis (BEA), with our baseline estimate, $\sigma_{\mathcal{D}}$.[54] Notably, the value of $\sigma_{\text{Actual}} = 0.0202$ aligns closely with the model-implied aggregate volatility $\sigma_{\mathcal{D}} = 0.0186$, suggesting that our model generates volatility of the correct order of magnitude.

Finally, we estimate the counterfactual volatility to be $\sigma_{\mathcal{C}} = 0.0247$, implying that aggregate output would have been $\approx 33\%$ more volatile between 1978 and 2017 (in response to natural disasters) in the absence of diverse firms' attenuation of shocks. This suggests that supply base diversity, in addition to minimizing output fluctuations at the microeconomic level, also substantially attenuates aggregate volatility. In conjunction with our empirical findings, our results imply that policymakers can smooth macroeconomic fluctuations by incentivizing firms to multi-source

[54] Specifically, σ_{Actual} is the standard deviation of quarterly year-on-year GDP growth over the period 1978-2017, measured using the BEA's quarterly real GDP series.

material inputs. Since multi-sourcing does not appear to have any consequential costs for firms in normal times and provides large benefits when there are supply disruptions, increasing supply base diversity may come at a minimal cost to firms while delivering large macroeconomic benefits.

C Proofs

Proof of Proposition 1. Throughout the proofs, we take the capital good as the numeraire, implying $r = 1$. First multiply both sides of Equation (B.1) 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 $b_i \equiv \frac{p_i c_i}{\text{GDP}}$. Noting that the specification of Cobb-Douglas preferences implies $d \log b_i = 0$ for all $i \in \mathcal{S}$, total differentiation of the above Equation yields

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

Next, the first-order condition with respect to intermediate input x_{km} purchased by firm k implies

$$\Omega_{km} = \frac{p_m x_{km}}{p_k y_k} = p_k^{\theta_s - 1} \omega_{km} p_m^{1-\theta_s}, \tag{C.2}$$

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 $\frac{\eta_k}{\lambda_k} = \frac{r k_k}{p_k y_k} = p_k^{\theta_s - 1} \mu_k z_k^{\theta_s - 1} r^{1-\theta_s}$. Consequently, by Equation (C.2) $d \log \Omega_{km} = (\theta_s - 1) [d \log p_k - d \log p_m]$, and plugging this equation into Equation (C.1) yields

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

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

$$d\log\boldsymbol{\lambda} = (\theta_{\mathcal{D}}-1)\mathrm{diag}\left(\boldsymbol{\lambda}\right)^{-1}\boldsymbol{\Psi}'\left(\boldsymbol{\Omega}'_{\mathcal{D}}\mathrm{diag}\left(d\log\mathbf{p}\right)-\mathrm{diag}\left(d\log\mathbf{p}\right)\boldsymbol{\Omega}'_{\mathcal{D}}\right)\boldsymbol{\lambda}_{\mathcal{D}} \\ +(\theta_{\mathcal{N}}-1)\mathrm{diag}\left(\boldsymbol{\lambda}\right)^{-1}\boldsymbol{\Psi}'\left(\boldsymbol{\Omega}'_{\mathcal{N}}\mathrm{diag}\left(d\log\mathbf{p}\right)-\mathrm{diag}\left(d\log\mathbf{p}\right)\boldsymbol{\Omega}'_{\mathcal{N}}\right)\boldsymbol{\lambda}_{\mathcal{N}}, \quad \text{(C.3)}$$

where $\mathrm{diag}(\mathbf{X})$ denotes a diagonal matrix with diagonal entries given by vector $\mathbf{X}$.

Next, we characterize $d\log\mathbf{p}$ in terms of the vector of capital-augmenting shocks $d\log\mathbf{z}$. 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 this 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 $r=1$, and given the expressions for Ω_{ij} and $\frac{\eta_i}{\lambda_i}$ derived earlier, we can write the above equation as

$$d\log p_i = -\sum_{h\in\mathcal{S}}\Psi_{ih}\frac{\eta_h}{\lambda_h}d\log z_h. \quad \text{(C.4)}$$

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 (C.3), yields

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

where $\mathbf{M}\equiv\mathrm{diag}\left(\boldsymbol{\Psi}\cdot\mathrm{diag}(\boldsymbol{\lambda})^{-1}\boldsymbol{\eta}\right)$ and $\circ$ denotes the Hadamard product. By taking the derivative of $\log\boldsymbol{\lambda}$ with respect to $\log z_j$, we get

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

which coincides with Equation (B.2). *Q.E.D*

Proof of Proposition 2. From the household's optimization problem, 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 $r = 1$ and the aggregate stock of capital is assumed to be in fixed supply. From the Divisia index for real GDP, $d\log Y = \sum_{k\in\mathcal{S}} b_k d\log c_k$, we get $\frac{d\log Y}{d\log z_i} = -\sum_{k\in\mathcal{S}} b_k \frac{d\log p_k}{d\log z_i}$. Using Equation (C.4), we can write $\frac{d\log Y}{d\log z_i} = \sum_{k\in\mathcal{S}} b_k \Psi_{ki} \frac{\eta_i}{\lambda_i} = \eta_i$, which uses the fact that $\sum_{k\in\mathcal{S}} b_k \Psi_{ki} = \lambda_i$.

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,

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

Finally,

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

Q.E.D

Proof of Proposition 3. Let $\Delta\log\tilde{Y}$ denote the change in real GDP up to a second-order approximation evaluated at $\theta_{\mathcal{N}} = 1$. More specifically,

$$\Delta\log\tilde{Y} = \boldsymbol{\eta}'\Delta\log\mathbf{z} + \frac{1}{2}\cdot\Delta\log\mathbf{z}'\text{diag}(\boldsymbol{\eta})\frac{d\log\boldsymbol{\eta}}{d\log\mathbf{z}}\bigg|_{\theta_{\mathcal{N}}=1}\Delta\log\mathbf{z},$$

where $\frac{d\log\boldsymbol{\eta}}{d\log\mathbf{z}}\Big|_{\theta_{\mathcal{N}}=1}$ is the matrix $\frac{d\log\boldsymbol{\eta}}{d\log\mathbf{z}}$ evaluated at $\theta_{\mathcal{N}} = 1$.

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

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

which is a consequence of Equation (B.2). By contrast, if $i\in\mathcal{D}$, then

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

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

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

we can write,

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

which is Equation (B.5). *Q.E.D*