Multisourcing and Supply Chain Disruptions*

Girish Bahal[§,†] Connor Jenkins[‡] Damian Lenzo[§]

[§] University of Western Australia

[‡] Bain & Company

[†] Centre for Applied Macroeconomic Analysis, ANU

Abstract

We study how the concentration of firms' intra-industry input purchases affects the transmission of supply chain disruptions through production networks. Empirically, we identify exogenous supply chain disruptions using natural disasters in the US. We find that firms with intermediate input purchases spanning many suppliers within an industry attenuate output declines by 55-70% following shocks to their suppliers. We show, causally, that multisourcing firms experience only modest output losses because i) a smaller proportion of their input mix is affected by shocks, and ii) they shift purchases towards unaffected suppliers of similar inputs. Our empirical findings align with the predictions of a canonical general equilibrium production network model, which we use to quantify the aggregate effects of multisourcing. At the macroeconomic level, the attenuation effects of multisourcing increase nonlinearly with the size of firm-level shocks and the degree of input substitutability.

JEL Codes: L25, D22, D57, E23

Keywords: Multisourcing, production networks, propagation of firm-level shocks

*This paper was previously circulated under the title "The Effect of Supply Base Diversification on the Propagation of Shocks". We are grateful to Toke Aidt, Enghin Atalay, Johannes Boehm, Vasco Carvalho, Arpita Chatterjee, Matthew Elliott, Apoorv Gupta, Lu Han, Michael Jetter, Bill Janeway, Callum Jones, Glenn Magerman, Julien Sauvagnat, Matthew Shapiro, Anand Shrivastava, Faisal Sohail, Saten Kumar, Ronald Peeters, Matthew Read and seminar participants at the Asia Meeting of the Econometric Society, Auckland University of Technology, Curtin University, Delhi School of Economics, Indian Institute of Management Bangalore, Indian Statistical Institute, Monash University, National Bank of Belgium, Reserve Bank of Australia, Reserve Bank of India, Reserve Bank of New Zealand, Singapore Management University, University of Auckland, University of New South Wales, University of Otago, University of Sydney, University of Western Australia, and Victoria University of Wellington for comments and suggestions.

Corresponding author information. Girish Bahal, UWA Business School, 35 Stirling Highway, Perth, WA, 6009, Australia. Email address: girish.bahal@gmail.com

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. 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). These examples highlight the potential for significant output losses when firms overly rely on a few suppliers, suggesting that multisourcing inputs can help firms insure against supply chain disruptions. While intuitive, there exists no systematic study on the effect of multisourcing intermediate inputs on the propagation of shocks.

Data and main results. We begin by conducting two intermediate empirical exercises. First, in a manner similar 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 listed US firms from 1978 to 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 examine how shocks propagate through supply chains, we use 52 major natural disasters in the US during the sample period to identify exogenous firm-level disruptions, following Barrot and Sauvagnat (2016). As a baseline, we find similar supplier-to-customer propagation effects as other studies in the literature.[1] Specifically, a firm's sales growth decreases by approximately three percentage points if at least one of its suppliers is hit with a natural disaster four quarters back.

After (re)establishing the propagation of supply shocks, we quantify the extent to which firms' multisourcing behavior insulates them against supplier shocks. We define two empirical measures of multisourcing: i) a weighted Herfindahl-Hirschman Index (HHI), which captures the degree of concentration of a customer firm's total input spending across its suppliers within 6-digit NAICS industries in a given quarter, and ii) a weighted sum of the customer's inverse number of suppliers within these industries. The weights in both cases correspond to a firm's intermediate inputs expenditure from an industry as a share of the firm's total input expenditure.

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

Firms classified as multisourcers according to either measure spread their input purchases across multiple suppliers *within* the same narrowly defined industry.[2] Notably, our multisourcing measures are not firm-specific, as a firm's supply base can change over time. We thus estimate the effect of multisourcing on shock propagation after purging out firm fixed effects, together with other time-varying firm-level controls. We find that multisourcing firms experience reductions in real sales growth that are, on average, 55-70% smaller than non-multisourcing firms when a major natural disaster hits at least one supplier four quarters earlier. Hence, we provide reduced-form empirical evidence that multisourcing similar intermediate inputs attenuates the propagation of supply shocks.

Mechanisms. Two mechanisms explain our reduced-form results: i) an *intensity* effect, where multisourcing reduces exposure to shocks by limiting reliance on any single supplier; and ii) a *substitution* effect, where firms reallocate purchases away from disrupted suppliers toward unaffected suppliers producing similar inputs. To test the intensity effect, we measure the proportion of a customer's inputs from each industry affected by a disaster using the HHI and supplier count approaches described above. Firms' *shock intensity* is defined as a weighted sum of the proportion of inputs affected across all supplier industries, with weights given by the customer's expenditure on inputs from each industry relative to their total input expenditure. We find that as the proportion of affected inputs tends toward zero, there is no impact on the customer's sales growth. The negative impact on sales growth increases as the proportion of affected inputs rises. At the extreme end, if nearly all of the inputs are affected by a disaster, the customer firm experiences a statistically and economically significant drop in year-on-year sales growth of approximately five percentage points.

To test the substitution mechanism, we examine 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 and easily substitutable inputs, an increase in expenditure on inputs from unaffected suppliers within the same industry is evidence that multisourcing firms attenuate shocks through substitution. First, we find that customer firms' input purchases from an affected supplier decline by approximately two percentage points following a major natural disaster. Second, purchases from unaffected suppliers increase by about three percentage points four quarters after a disaster strikes another supplier within the same industry. The timing of substitution coincides with when we observe the greatest attenuation by multisourcing firms, indicating that supply shock propagation

[2]The distribution of buyer-supplier connections in Compustat exhibits significant dispersion, meaning there is considerable variation in firms' degree of multisourcing. Similarly, Bernard et al. (2022) show that buyer-supplier connections in Belgium are also highly dispersed.

is significantly mitigated when customer firms multisource inputs and substitute across similar suppliers.

Ruling out alternative explanations and other robustness checks. We conduct multiple checks to assuage concerns that may confound our analysis. For example, we show that the trends in sales growth of multi- and non-multisourcing firms are very similar *before* the occurrence of a supply shock. Hence, the difference in sales growth following a supply shock can be attributed to differences in firms' level of multisourcing and not pre-existing trends. Next, we address the issue raised by a recent and growing literature on heterogeneous difference-in-differences which cautions against making "forbidden comparisons" in complicated treatment setups where the "treatment" occurs over multiple periods and can switch on and off over treated units (firms in our case).[3] We show that our results are robust to incorporating event study designs suggested by this literature.

Another concern is that firms may endogenously choose their level of multisourcing in response to supply shocks. If firms increase their level of multisourcing when they or their suppliers are hit by a disaster, our estimates may overstate the attenuation effects of multisourcing. This is because what appears as shock mitigation due to multisourcing 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 firms' level of multisourcing is not explained by the frequency of disasters hitting customer firms or their suppliers, suggesting that firms do not systematically multisource in response to direct or indirect supply disruptions.[4] 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.[5]

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, suggesting that firms do not systematically base their input-sourcing decisions on suppliers' proneness to disasters.

[3] See, for example, de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Borusyak et al., 2024, among others.

[4] Consistent with our results, Balboni et al. (2024) find that firms do not persistently increase their number of suppliers following a flood to their own premises or those of their existing suppliers.

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

Next, we address the concern that the level of multisourcing may be correlated with customers' bargaining power over their suppliers. Specifically, multisourcing firms may be large firms that source similar inputs from multiple smaller suppliers. If affected suppliers prioritize serving their most important customers (multisourcing firms), then the attenuation effects we estimate may reflect the benefit of greater bargaining power, rather than the effect of multisourcing similar inputs. To address this, we use a measure of customer firms' bargaining 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 firms' level of multisourcing remain after controlling for firms' bargaining power.

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

The above checks help establish that the attenuation of supply shocks by customer firms is due to their ex-ante level of multisourcing, 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 multisourcing (from a theoretical or an empirical standpoint). While this question is important for future research, it is outside the scope of this paper. Our objective, instead, is to empirically and analytically examine how multisourcing similar production inputs insulates firms against supply chain disruptions.

Conceptual framework and quantitative results. We show that our main empirical results are consistent with the predictions of a canonical general equilibrium production network model, in the spirit of Acemoglu et al. (2012) and Balboni et al. (2024). The model features a set of narrowly defined industries, each populated with a finite number of firms that produce near-identical products. Firms' output is consumed by the representative household as final demand and by other firms as intermediate inputs. Firms vary in the extent to which they multisource inputs from each supplier industry. Similar to the empirics, we measure firms' level of multisourcing based on the concentration of their intermediate input purchases across suppliers within each industry.

We first characterize how a (customer) firm's real output changes in response to an idiosyncratic supply shock to a single supplier. We show that the decline in a customer's output is smaller when it multisources inputs from the affected industry, and that the two mechanisms identified in the empirics–intensity and substitution effects–explain this result. As noted above, the intensity effect states that multisourcing firms are less affected, as only a portion of their inputs are disrupted, unlike firms that rely on a single supplier for their inputs. Notably, the substitution effect depends on the *interaction* between the elasticity of substitution between intermediates *and* the degree to which firms' multisource inputs. For a given shock, the substitution effect is greater when i) the elasticity of substitution is higher and ii) the concentration of firms' input purchases is lower at the initial equilibrium. If the customer firm has alternative suppliers within the affected industry, it can easily redistribute its input purchases across these suppliers, mitigating the supply disruption to a greater extent.

Second, we derive a formula for the aggregate effect of a supplier shock in terms of firms' level of multisourcing. The aggregate effect is the sum of direct and indirect effects: the direct effect captures the reduction in final consumption of the shocked firm's output, while the indirect effect reflects the decline in final consumption of its customers' output. Consistent with our first results, the direct and indirect effects are in turn made up of the intensity and substitution effects. Both the direct and indirect effects increase with the intensity of the shock. In the extreme case, if all firms single-source inputs from the shocked firm, then the pass-through of the shock is most pronounced. Conversely, when firms multisource and can substitute inputs, the macroeconomic impact of a supply shock is significantly mitigated.

Finally, we use our model to quantify the macroeconomic effects of multisourcing. In a preliminary exercise, we use the model to estimate the elasticity of substitution between intermediates within 6-digit NAICS industries. In line with our empirical results, we find evidence of gross substitutability between intermediates, with our preferred specification yielding an elasticity of 3.3.[6] We then use the model to bound the effect of idiosyncratic production disruptions on GDP growth, assuming that at one extreme, firms do not multisource intermediate inputs, while at the other, firms fully diversify their input purchases within industries. Our results suggest that multisourcing can substantially attenuate the macroeconomic impact of microeconomic shocks: multisourcing reduces the decline in aggregate output by up to 90%. Second, the macroeconomic effects of multisourcing are nonlinear: when shocks are larger, the attenuation effects on real GDP are more pronounced. Finally, we show that substitution effects are significant at the macroeconomic level. When firms can more easily substitute affected inputs, shock attenuation at the macroeconomic level approximately doubles.

[6]This estimate broadly aligns with other studies in the literature (Broda and Weinstein, 2006; Peter and Ruane, 2023; Carvalho et al., 2021).

2 Related literature

Our paper is 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' multisourcing behavior instead of supplier characteristics. We find the transmission of shocks from suppliers to customers is attenuated for firms that multisource. This finding is not in contradiction with Barrot and Sauvagnat (2016); as we discuss in Section 3.6, input specificity and multisourcing are both important drivers of the transmission of supply shocks within the production network.

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. 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. We contribute to this literature by empirically showing that, in line with the model's predictions, i) multisourcing firms are insulated from natural disasters affecting their suppliers, and ii) intensity and substitution effects explain why these firms perform better in response to supplier shocks.[7] Our paper also relates to recent literature on firms' responses to supply chain risks, including Khanna et al. (2022), Balboni et al. (2024), Blaum et al. (2024), Pankratz and Schiller (2023) and Castro-Vincenzi (2024), among others. We contribute to this literature by identifying a new firm characteristic (multisourcing) that influences the propagation of supply shocks. We also develop a framework to explain why multisourcing firms are insulated from such shocks.

Our paper is also related to the theoretical literature that studies the role of input-output linkages in the propagation of microeconomic shocks, such as Long and Plosser (1983), Acemoglu et al. (2012), and Kopytov et al. (2024), among others.[8] While much

[7]Relatedly, Boehm and Sonntag (2023) find that, in response to mergers, firms experience a significant decline in sales when cut off from one of their suppliers. This decline is less severe if the firm has alternative suppliers within the same industry.

[8]Early contributions to this topic include 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. Studies such as Elliott et al. (2022) and Carvalho et al. (2022) study how complex supply chains and bottlenecks can contribute to

of the literature has focused on input-output linkages as a source of shock amplification, we examine how firms' input-sourcing behavior can mitigate the propagation of shocks through the network. We identify two distinct mechanisms that explain why multisourcing firms attenuate supply shocks (intensity and substitution effects) and show that both prevent sharp declines in output at the microeconomic and macroeconomic levels.[9]

We use a disaggregated multi-sector macroeconomic model à la Acemoglu et al. (2012); Atalay (2017) and Baqaee and Farhi (2019) to characterize changes in both micro- and macroeconomic output, up to a second-order approximation, in response to idiosyncratic supply shocks. We extend the standard model by introducing firm-supplier industry measures of multisourcing, demonstrating that the *interaction* between firms' degree of multisourcing and the elasticity of substitution between intermediates within narrowly defined industries determines the extent of shock propagation. Even with low elasticities of substitution, multisourcing can still significantly attenuate supply shocks. Our macroeconomic results also reveal that changes in real GDP are proportional to firms' intensity and substitution effects, implying that increases in firms' level of multisourcing limit the aggregate impact of microeconomic shocks.[10,11]

3 Empirical results

Section 3.1 describes the data used in the empirical analysis. Section 3.2 (re)establishes that natural disasters, which represent plausibly exogenous production disruptions, not only directly impact suppliers' sales growth but also reduce the sales growth of their customers. Section 3.3 discusses how we measure multisourcing using information from Compustat's *Customer Segements* files. Section 3.4 presents our benchmark empirical results. In Section 3.5, we identify the mechanisms that explain *how* multisourcing firms attenuate supply shocks. Finally, in Section 3.6, we rule out some alternative explanations of our results.

macroeconomic fragility. See Carvalho (2014) and Carvalho and Tahbaz-Salehi (2019) for a thorough review of the literature on production networks.

[9]Our paper is also related to the growing theoretical literature on policies aimed at building supply chain resilience, such as Grossman et al. (2023, 2024).

[10]We also contribute to the literature exploring the implications of non-unitary elasticities of substitution on the propagation of shocks (e.g., Horvath, 2000, Atalay, 2017, and Baqaee and Farhi, 2019). Using our model, we estimate a within-industry elasticity of substitution greater than one, implying that, to a second-order approximation, negative supply shocks are attenuated by multisourcing firms.

[11]A separate literature in international trade studies 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 diversification at the country level, we are the first (to the best of our knowledge) to examine how multisourcing affects economic activity at the level of the firm.

3.1 Data and summary statistics

We briefly discuss the data used in our empirical analysis and provide additional details in Appendix B. We use quarterly firm-level financial data from Compustat's *North America Fundamentals Quarterly* database (1978-2017) for information on publicly listed firms' sales, cost of goods sold (COGS), industry classification (NAICS), and locations (ZIP codes).[12] We use Compustat's *Customer Segments* dataset to identify active supplier-customer relationships. This dataset provides information on the identities of suppliers and customers and the sales to each customer. Information on customer-supplier links is based on Financial Accounting Standard No. 131, which requires US public firms to report the identities of major customers that account for 10% or more of their total revenues. Notably, the 10% threshold does not bias the in-degree (number of suppliers) distribution of firms in our sample (see Atalay et al., 2011).[13] This is important because we use information on the number of suppliers (not customers) to compute empirical measures of multisourcing, meaning that our measures are not biased by the 10% reporting threshold. Nonetheless, in Section 3.6, we present additional robustness tests to highlight that the reporting threshold does not affect our estimates of the effect of multisourcing on shock propagation. 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-side effect the disaster may have had on the customer firm.[14] As examples, the top panel of Figure 1 shows the supplier-customer production network for 1978 and 2017. Similarly, we construct production networks for all periods in our sample. The bottom panel shows the geographical dispersion of the firm-level production network for 1978 and 2017. Notably, a significant proportion of customer-supplier links are inter-state, providing an ideal setting to examine how multisourcing affects the propagation of shocks.

We use natural disaster data from EM-DAT and the Federal Emergency Management Agency's (FEMA) *OpenFEMA Disaster Declarations* datasets to identify exogenous disruptions to firms' production. Consistent with Barrot and Sauvagnat (2016), we include all disasters with damages exceeding $1 billion (adjusted to 2017 USD) that lasted less than 30 days. There are 52 major natural disasters in our sample. Appendix Figure A.3 shows that many of the disasters in our sample 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 disasters' localized and random nature makes

[12] Appendix Figure A.1 illustrates the dispersion of firm headquarters over the entire sample period on a county-level US map.

[13] The distribution of customer firms' in-degrees (number of suppliers) is positively skewed, with a median supplier count of 10, a mean of 21.3, and the maximum number of suppliers exceeding 100 (see Appendix Figure A.2).

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

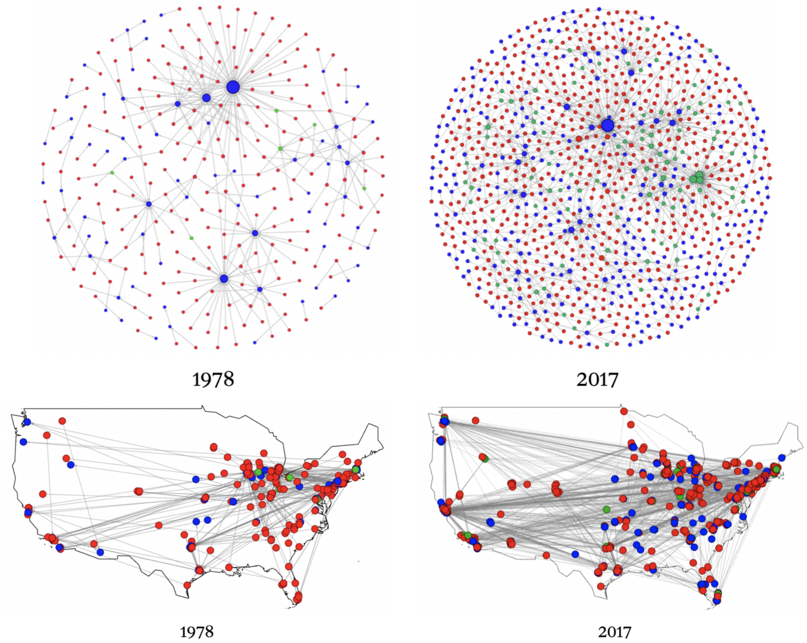

Figure 1: Comparison of US Supply Network (1978 & 2017)

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.

them plausibly exogenous supply shocks. 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.

Table 1 presents summary statistics for the sample of firms used in our analysis. Panel A describes the supplier sample, which includes ≈ 5,000 firms generating ≈ 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. On average, never-treated and eventually treated suppliers have comparable sales growth, COGS growth, and number of customers. Eventually-treated firms are slightly larger (in terms of total assets and number of employees), have higher returns on assets, and are older than never-treated firms. Among eventually treated firms, there is a 4% chance a supplier will be hit with a disaster in any given quarter.

Panel B presents the customer sample, comprising ≈ 2,000 firms and ≈ 95,000 customer-

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.

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 customer firms whose suppliers are never affected by a disaster. Treated and never-treated customer firms have similar sales growth, COGS growth, distance to suppliers, and probabilities of being directly affected by natural disasters. Like in the supplier sample, eventually treated customers are larger (in terms of total assets, number of employees, and number of suppliers), slightly more productive (in terms of return on assets), and older relative to never treated firms. This is logical, as larger firms typically have more suppliers and are, thus, more likely to experience supply disruptions. Finally, the probability that a disaster hits the supplier of an eventually-treated customer is 4%.

As we explain in detail in the following sections, our regressions include firm fixed effects and time-varying controls such as firm size, return on assets, age, and supplier count to ensure that other firm characteristics do not confound our results. Importantly, as we show in Section 3, there are no discernible pre-trends between treated and untreated firms (where treatment refers to either a disaster affecting the firm itself or its supplier).

Similarly, we demonstrate that multi- and non-multisourcing firms exhibit similar pre-trends, allowing us to estimate the effect of multisourcing on the propagation of shocks.

3.2 The direct and indirect effects of natural disasters

We begin by identifying exogenous supply disturbances that a) directly affect firms' supply operations and b) indirectly disrupt their customers. We identify supply shocks by the occurrence of major natural disasters in the counties where firms' headquarters are located. These findings, originally established by Barrot and Sauvagnat (2016), are revalidated in our context.[15] Equation (1) estimates how the growth in real sales, relative to the same quarter in the previous year, $\Delta \log Q_{iI,t}$, changes if the firm is directly hit by a disaster. Here $Q_{iI,t}$ refers to real sales (in dollar terms) of firm i in industry I at quarter t.[16]

$$\Delta \log Q_{iI,t} = \alpha + \sum_{k=-4}^{10} \beta_k \cdot \mathbb{I}[\text{Shock hits } iI]_{t-k} + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t}. \tag{1}$$

The indicator $\mathbb{I}[\textit{Shock hits iI}]_{t-k}$ takes the value one when the county in which firm iI is located is hit by a natural disaster at time $t-k$, and zero otherwise. 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_{iI} 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.[17] 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.[18] Throughout the paper, all regressions include controls for firms' number of employees and age. Finally, we also control for fiscal-quarter fixed effects.[19] All controls not explicitly shown in Equation (1) are represented by the vector $\mathbf{X}_{iI,t}$. Equation (1) is estimated using the supplier sample.

$$\Delta \log Q_{iI,t} = \alpha + \sum_{k=-4}^{10} \beta_k \cdot \mathbb{I}[\text{Shock hits } iI]_{t-k} + \sum_{k=-4}^{10} \gamma_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t}. \tag{2}$$

[15]See Barrot and Sauvagnat (2016) for a series of additional robustness tests on the direct and propagation effects of natural disasters.

[16]We deflate firms' sales using the GDP price index from the Bureau of Economic Analysis.

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

[18]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).

[19]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.

To estimate the propagation of natural disaster shocks, we estimate Equation (2) using the customer sample.[20] Equation (2) is essentially the same as Equation (1) but with an additional variable, $\mathbb{I}[\textit{Shock hits iI's supp.}]_{t-k}$, which takes a value of one if at least one supplier of the customer firm iI 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 continue to control for $\mathbb{I}[\textit{Shock hits iI}]_{t-k}$.[21]

Appendix Figure A.4 summarizes the results. The orange line shows the direct impact of the disaster on firms (β_k's from Equation 1), whereas the blue line shows how the shocks propagate from affected suppliers to their customers (γ_k's from Equation 2). The direct effect is most pronounced two quarters after the event, when firms' year-on-year sales growth declines by 6.4 percentage points (pp). This decline in sales growth is economically significant, corresponding to a 33% decrease in average sales growth. The indirect effects are consequential as well. Customer firms whose suppliers are hit by a natural disaster experience the greatest decline in sales growth (-3.1pp) four quarters after a supplier is hit by a shock. This amounts to a 31% decline in average sales growth in the customer sample. Figure A.4 also shows that it is not pre-existing trends driving the change in customer sales growth but rather the effects of disruption to their supplier(s). The direct and indirect effects of natural disasters normalize after 8-10 quarters.[22] The size and timing of the direct and indirect effects of natural disasters on firms' performance are consistent with the existing literature on the topic.[23] These baseline results establish that production disruptions propagate from suppliers to customers.[24]

[20] Consistent with Barrot and Sauvagnat (2016), we re-estimate regression (2), replacing sales growth (which measures the market value of goods sold) with growth in the cost of goods sold (COGS) as the dependent variable. We find that customers' COGS growth declines following shocks to suppliers, suggesting that shock propagation is driven by customers receiving fewer inputs rather than changes in suppliers' prices after a natural disaster. If suppliers' prices adjust in response to shocks, we would expect customers' COGS to increase. See Barrot and Sauvagnat (2016) for details. Results on COGS are available upon request.

[21] The vector $\mathbf{X}_{iI,t}$ includes the same set of controls as Equation (1), as well as a control for firms' number of suppliers.

[22] Overall, the maximum direct and indirect effects of natural disasters on firms' performance occur at lags 2 and 4, respectively. This is consistent with what one might expect; firms likely have excess inventory, which buffers the initial effects of reduced production on sales (Hendricks et al., 2009).

[23] 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 shocks from the 2011 Japanese Earthquake.

[24] Appendix Table A.1 presents estimates for Equation (2) but with an additional indicator that takes the value one if an *eventually (but not currently) linked* supplier is hit by a disaster at $(t-4)$, and zero otherwise. This allows us to test whether supplier shocks affect customer firms when the customer-supplier

3.3 Empirical measures of multisourcing

In this section, we define two empirical measures of multisourcing. Each measure is constructed using data from Compustat's *Customer Segments* files. Throughout, N_J denotes the set of firms in industry J, and jJ represents a firm j belonging to industry J.

Measure 1. Our first measure captures how firm iI allocates its input purchases among all its suppliers within 6-digit NAICS industries. We measure the concentration of firm iI's purchases across inputs from industry J using the HHI:

$$\mathcal{M}^{J}_{iI,t} = \sum_{j \in N_J} \left(\frac{\text{Input Purchases}^{jJ}_{iI,t}}{\text{Total Input Purchases}^{J}_{iI,t}} \right)^2, \tag{3}$$

where *Input Purchases*$^{jJ}_{iI,t}$ is firm iI's nominal expenditure on inputs from firm j in industry J in quarter t and *Total Input Purchases*$^{J}_{iI,t}$ is iI's total input expenditure across all its suppliers in industry J in quarter t.[25] Next, we take the weighted average of Equation (3) across all supplier industries of firm iI in quarter t:

$$\mathcal{M}^{\text{HHI}}_{iI,t} = \mathbb{E}_{\Theta}\left[\mathcal{M}^{J}_{iI,t}\right], \tag{4}$$

where $\mathbb{E}_{\Theta}[\cdot]$ denotes the weighted average of $\mathcal{M}^{J}_{iI,t}$ for $J = 1, \ldots, N$ where the weight $\Theta^{J}_{iI,t}$ represents the expenditure of the firm iI on intermediate inputs from industry J, as a share of $iI's$ total intermediate input expenditure.

Therefore, $\mathcal{M}^{\text{HHI}}_{iI,t}$ can be thought of as firm iI's average level of multisourcing at quarter t. Firms with low values of $\mathcal{M}^{\text{HHI}}_{iI,t}$ 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 3.5, 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 $\mathcal{M}^{\text{HHI}}_{iI,t} = 1$, firm iI acquires all its recorded inputs from a single firm within each supplier industry. We define an indicator $\mathbb{I}[iI\ \textit{Multisources}^{\text{HHI}}]_t$ that takes a value one for firms that fall in the bottom tercile of $\mathcal{M}^{\text{HHI}}_{t}$ across all firms over a quarter, and zero otherwise.[26]

relationship is inactive. Crucially, the table shows that propagation only occurs when there is an *active* customer-supplier relationship.

[25] Input purchases data is reasonably well-populated in the *Customer Segments* files, with only approximately six percent of observations missing.

[26] In Section 3.6, we discuss how the measurement error induced by the 10% reporting rule discussed in Section B.3 is unlikely to be a cause for concern as it works against finding any impact of multisourcing on shock propagation.

Measure 2. Our second measure of multisourcing is based on supplier counts rather than input expenditure shares:

$$\mathcal{M}^{J}_{iI,t} = \frac{1}{N^{J}_{iI,t}}, \tag{5}$$

where $N^{J}_{iI,t}$ is the number of suppliers of firm iI from industry J at quarter t. We then take the weighted average of Equation (5) using the industry-level intermediate share weights as in (4):

$$\mathcal{M}^{\text{Count}}_{iI,t} = \mathbb{E}_{\Theta}\left[{N^{J}_{iI,t}}^{-1}\right]. \tag{6}$$

The measure $\mathcal{M}^{\text{Count}}_{iI,t}$ takes a low value if, on average, firm iI has many suppliers from each industry J from which it purchases inputs. Conversely, $\mathcal{M}^{\text{Count}}_{iI,t} = 1$ if firm iI has only one supplier from each industry at quarter t. The measure $\mathcal{M}^{\text{Count}}_{iI,t}$ assigns equal weight to all of firm iI's connections within a supplier industry, emphasizing that it is the availability of alternative suppliers that matters to meet iI's input demand if one supplier is hit by a shock. As above, we define an indicator $\mathbb{I}[iI\ Multisources^{\text{Count}}]_t$ that takes a value one for firms that fall in the bottom tercile of $\mathcal{M}^{\text{Count}}_t$ across all firms over a quarter, and zero otherwise.

Appendix Figure A.5 shows the distributions of supplier counts within 6-digit NAICS industries for multi- and non-multisourcing firms, as identified by our two empirical measures. Approximately 80% of multisourcing firms purchase inputs from at least two suppliers within the same 6-digit NAICS industry. In contrast, non-multisourcing firms, on average, source inputs from 1.11 (median = 1) suppliers within a 6-digit NAICS code.

3.4 The effect of multisourcing on the propagation of shocks

We now test whether multisourcing intermediate inputs protects firms against supply chain disruptions. For this, we run the following reduced-form specification:

$$\begin{aligned}
\Delta \log Q_{iI,t} &= \alpha + \sum_{k=-4}^{10} \beta_k \cdot \mathbb{I}[\text{Shock hits } iI]_{t-k} + \sum_{k=-4}^{10} \gamma_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} \\
&\quad + \sum_{k=-4}^{10} \kappa_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} \times \mathbb{I}[iI \text{ Multisources}]_t \\
&\quad + \delta \cdot \mathbb{I}[iI \text{ Multisources}]_t + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t}.
\end{aligned} \tag{7}$$

Equation (7) is the same as Equation (2) but with two additional regressors. The variable $\mathbb{I}[iI\ Multisources]_t$ represents one of the two multisourcing indicators defined in Section 3.3. We run separate regressions for each multisourcing measure and omit the superscript for notational convenience. The interaction $\mathbb{I}[Shock\ hits\ iI\text{'s}\ supp.]_{t-k} \times \mathbb{I}[iI\ Multisources]_t$ takes the value one if a natural disaster hits a "multisourcing" firm's supplier. We interact the various leads and lags of $\mathbb{I}[Shock\ hits\ iI\text{'s}\ supp.]_{t-k}$ with multisourcing dummies at time t, as customer firms attenuate supplier shocks once these shocks propagate.[27] The coefficients of interest, κ_k's, estimate the average difference in sales growth of multi- and non-multisourcing firms when at least one supplier is hit by a natural disaster.

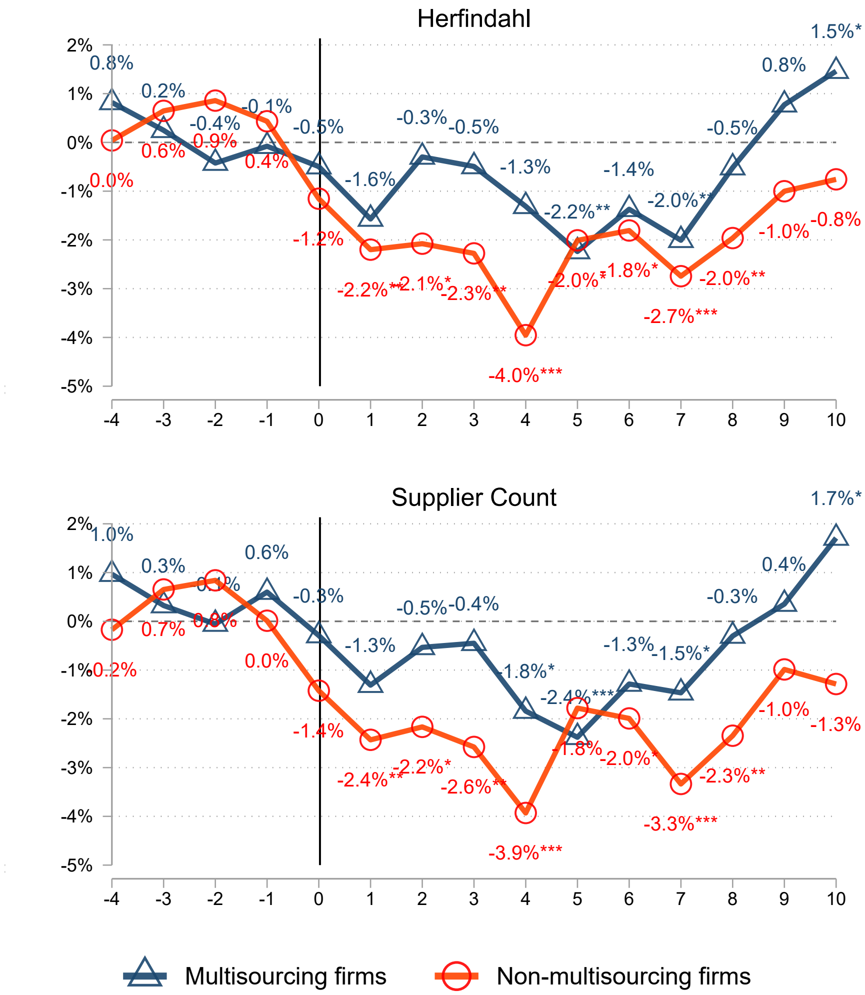

Figure 2: The Effect of Multisourcing on the Propagation of Shocks

Note: This figure presents estimates relating to regression specification (7). The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. In the top panel, multisourcing is measured using firms' supplier HHIs (Equation 4). In the bottom panel, multisourcing is measured using supplier counts (Equation 6). The blue lines plot estimates of the propagation effect of supply chain disruptions on multisourcing firms' sales growth (i.e., $\hat{\gamma} + \hat{\kappa}$ in Equation 7), while the orange lines show the propagation effect on non-multisourcing firms' sales growth (i.e., $\hat{\gamma}$). All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and control variables for firms' number of employees, number of suppliers and age. The regressions also include 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.

[27] Our results are robust to interacting the multisourcing dummies at the time of the shocks (Appendix Figure A.6).

The results relating to Equation (7) are presented in Figure 2. The blue lines show the *propagation* effect of supply chain disruptions on multisourcing firms' sales growth (i.e., $\hat{\gamma} + \hat{\kappa}$ in Equation 7), while the orange lines represent the propagation effect on non-multisourcing firms' sales growth (i.e., $\hat{\gamma}$). The top panel presents estimates relating to the HHI measure of multisourcing. The figure shows that non-multisourcing firms experience a decline in sales growth of 2.2pp, significant at the 5% level, one quarter after the shock, reaching a maximum decline of 4pp (significant at the 1% level) after four quarters. For these firms, sales growth returns to pre-shock levels after approximately 10 quarters. In contrast, the propagation of supply chain disruptions to multisourcing firms is substantially attenuated. After one quarter, multisourcing firms' sales growth declines by a statistically insignificant 1.6pp and by 1.3pp after four quarters. The effect on multisourcing firms' sales growth reaches a maximum decline of 2.2pp five quarters after a natural disaster hits a supplier and recovers after approximately eight quarters. At the fourth lag, when the propagation to non-multisourcing firms is at its greatest, multisourcing firms experience a decline in sales growth that is approximately 70% smaller than that of non-multisourcing firms.[28]

As shown in the bottom panel of Figure 2, we find similar results for the multisourcing measure based on supplier count. Specifically, while non-multisourcing firms experience an average sales growth decline of 2.4pp, significant at the 5% level, after one quarter, multisourcing firms' sales growth declines by a statistically insignificant 1.3pp. After four quarters, non-multisourcing firms' sales growth declines by 3.9pp (significant at the 1% level), whereas multisourcing firms' sales growth declines by only 1.8pp (significant at the 10% level). Multisourcing firms experience a delayed but modest decline in sales growth of 2.4pp after five quarters, recovering to pre-shock levels after eight quarters, while non-multisourcing firms recover after approximately nine quarters. At the fourth lag, the decline in sales growth for multisourcing firms is approximately 55% smaller compared to non-multisourcing firms. Our results suggest that multisourcing firms significantly mitigate supply chain disruptions.[29]

The variation we use to identify the attenuation effect of multisourcing is seemingly idiosyncratic. Appendix Figure A.8 shows that our multisourcing measures are orthogonal to various firm attributes one might expect to influence firms' input-sourcing deci-

[28]The sharpest decline in sales growth for multisourcing firms (at lag 5), is still approximately 50% smaller than the maximum decline of 4pp (at lag 4) for non-multisourcing firms.

[29]We test whether our findings in Figure 2 are robust to the inclusion of extra controls. Appendix Figure A.7 presents estimates for specification (7) but with the progressive inclusion of firm, time, size, return on assets (ROA) by quarter, state-time, and industry-time fixed effects and control variables for firms' number of suppliers and level of inventory. Our key empirical finding that multisourcing firms attenuate shocks is robust to the inclusion of these controls.

sions.[30] Of course, there may be unobserved characteristics that can explain this residual identifying variation. For example, managers' industry connections may influence input sourcing decisions (Patault and Lenoir, 2024). We do not aim to explain all of the identifying variation in multisourcing across firms. Instead, we require that multisourcing and non-multisourcing firms exhibit parallel trends, meaning that the sales growth dynamics of the two groups are not systematically different prior to treatment. Figure 2 shows that, for each measure, multisourcing and non-multisourcing firms have nearly identical sales growth dynamics before a disaster hits a supplier. This suggests that the attenuation of supply shocks by multisourcing firms is not attributable to pre-existing trends. The sales growth dynamics before the shock provide further evidence that multi- and non-multisourcing firms do not differ systematically, except in their levels of multisourcing. In the next section, we go one step further and causally identify the mechanisms that explain why multisourcing firms attenuate supply shocks.

3.5 Mechanisms

Our results in the previous section provide reduced-form evidence that multisourcing firms cope better in response to supply shocks relative to firms that do not multisource inputs. In this section, we provide empirical evidence on the mechanisms that explain this result. Intuitively, there are two plausible mechanisms: i) firms that multisource respond better to supply shocks because a smaller proportion of their inputs are disrupted by disasters (the *intensity effect*); and ii) multisourcing firms are better able to shift purchases from affected to unaffected suppliers producing similar inputs (the *substitution effect*).

The intensity effect. We measure the intensity of supplier shocks in two ways. Our first measure uses information on input purchases from the *Customer Segments* files:

$$\text{Proportion of Inputs Affected}^{J}_{iI,t} = \sum_{j \in N_J} \left(\frac{\text{Input Purchases}^{jJ}_{iI,t}}{\text{Total Input Purchases}^{J}_{iI,t}} \right) \times \mathbb{I}[\text{ Shock Hits Supplier } jJ]_t, \tag{8}$$

where $\mathbb{I}[$ *Shock Hits Supplier* $jJ]_t$ is an indicator that takes the value one if supplier j in industry J was hit by a shock at quarter t. The variable $0 \leq \textit{Proportion of Inputs Affected}^{J}_{iI,t} \leq 1$ measures the intensity with which firm iI's inputs from industry J are impacted by shocks. A higher value indicates that a greater proportion of firm iI's inputs from industry J are affected. Since firm iI sources inputs from multiple industries, we compute the weighted average of Equation (8) across all industries supplying iI with intermediate

[30] Specifically, we regress each multisourcing indicator on a different firm characteristic and all controls in specification (7). As shown in Appendix Figure A.8, we do not find any significant correlation between our multisourcing 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.

goods:

$$\text{Shock Intensity}^{\text{Input}}_{iI,t} = \mathbb{E}_{\Theta}\left[\text{Proportion of Inputs Affected}^{J}_{iI,t}\right]. \tag{9}$$

The variable *Shock Intensity*$^{\text{Input}}_{iI,t}$ takes a high value when, on average, a large proportion of iI's inputs from different industries are affected by shocks.

Our second measure uses information on the number of a firm's suppliers affected by natural disasters within each industry, assuming that each supplier within an industry is equally important to firm iI:

$$\text{Proportion of Suppliers Affected}^{J}_{iI,t} = \sum_{j \in N_J} \frac{1}{N^{J}_{iI,t}} \times \mathbb{I}[\text{ Shock Hits Supplier } jJ]_t. \tag{10}$$

Equation (10) measures the proportion of firm iI's suppliers from industry J that are affected by natural disasters in quarter t; attaching an equal weight $(1/N^{J}_{iI,t})$ to each supplier from industry J. We define *Shock Intensity*$^{\text{Count}}_{iI,t}$ in Equation (11) by taking a weighted sum of the proportion of suppliers affected in each industry J in quarter t by firm iI's input purchases share from industry J at time t:

$$\text{Shock Intensity}^{\text{Count}}_{iI,t} = \mathbb{E}_{\Theta}\left[\text{Proportion of Suppliers Affected}^{J}_{iI,t}\right]. \tag{11}$$

To test whether firms' customers are more adversely affected when a greater proportion of inputs/suppliers are impacted by shocks, we run the following regression:

$$\begin{aligned}\Delta \log Q_{iI,t} = \alpha &+ \sum_{k=0}^{4} \beta_k \cdot \mathbb{I}[\text{Shock hits } iI]_{t-k} + \sum_{k=0}^{4} \gamma_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} \\ &+ \sum_{k=0}^{4} \kappa_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} \times \text{Shock Intensity}_{iI,t-k} + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t}. \end{aligned} \tag{12}$$

Shock Intensity is centered around its mean so $\hat{\gamma}_k$ represents the impact of a supply shock at the average shock intensity. We run separate regressions for each (demeaned) *Shock Intensity* measure, omitting superscripts for notational simplicity.[31,32] Given $\hat{\gamma}$'s, $\hat{\kappa}$'s, and the average level of shock intensity, we estimate the impact of supply shocks at varying levels of *Shock Intensity*, and plot the results in Figure 3. The left- and right-hand panels correspond to the *Shock Intensity* measures defined in Equations (9) and (11), respectively. The coefficient estimates plotted at 0% of inputs/suppliers affected are $\hat{\gamma}_k - \hat{\kappa}_k \times$ *Avg. Shock*

[31] We focus on the first four lags for visibility, as propagation effects reach a maximum at lag four (as shown in Figure 2), though we find similar patterns beyond the fourth lag as well.

[32] Each regression also includes firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and control variables for firms' number of suppliers, number of employees, age, size and return on assets.

Intensity, while the estimates at 100% are $\hat{\gamma}_k + \hat{\kappa}_k \times$*(1 - Avg. Shock Intensity)*, and so on.

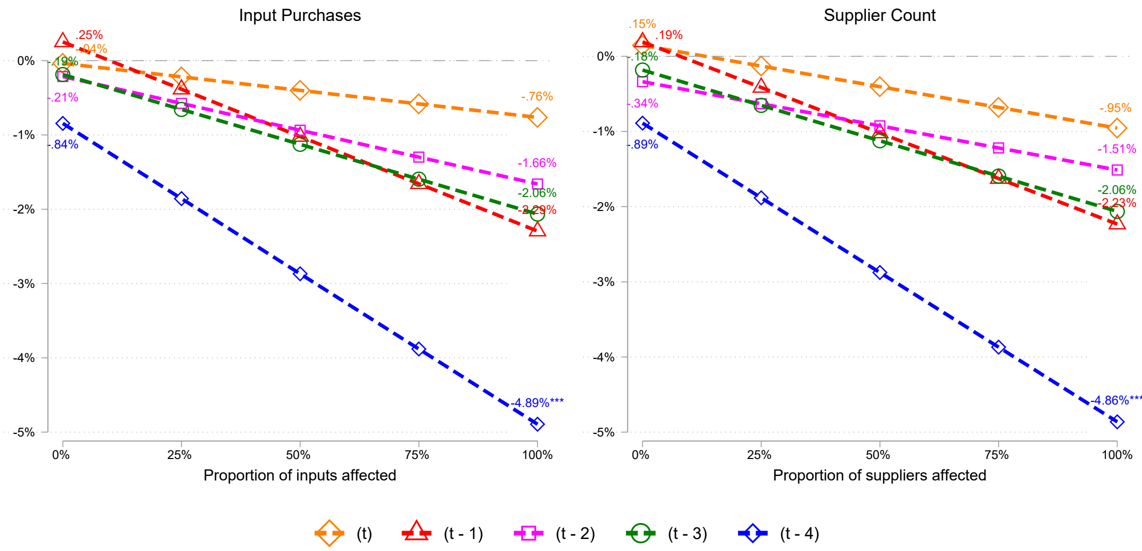

Figure 3: Proportion of Affected Inputs/Suppliers and the Propagation of Shocks

Note: This figure presents estimates relating to regression specification (12). The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. In the left panel, *Shock Intensity* is measured using information on input purchases, as in Equation (9), whereas in the right panel, it is measured using supplier counts, as in Equation (11). Estimates for 0% of inputs/suppliers affected by shocks correspond to $\hat{\gamma}_k - \hat{\kappa}_k \times$ *Avg. Shock Intensity*, where $\hat{\gamma}_k$ and $\hat{\kappa}_k$ are from Equation (12). Estimates for 100% of inputs/suppliers affected correspond to $\hat{\gamma}_k + \hat{\kappa}_k \times$ *(1 - Avg. Shock Intensity)*, and so on. 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, age, size and return on assets. Standard errors are clustered at the firm level. *10%; **5%; ***1% significance levels.

The figure reveals three key findings. First, at each lag, the decline in sales growth increases with the proportion of inputs/suppliers affected by natural disasters, as indicated by the negative slope of each trend line. Second, the greatest impact on customer firms occurs four quarters after a supply chain disruption (blue lines in each panel). When 100% of inputs or suppliers are affected, customer firms' sales growth declines by 4.89pp or 4.86pp, depending on the measure of shock intensity. This corresponds to an approximately 50% decline in sales growth relative to the mean sales growth of customer firms. Finally, as the proportion of inputs/suppliers affected tends to zero, the sales growth of customer firms is unaffected by shocks. For all lags, the effect of $\approx 0\%$ of inputs/suppliers affected is statistically insignificant from zero. Taken together, the results in Figure 3 show that firms' output declines more significantly when a greater proportion of their input purchases or suppliers are simultaneously affected by natural disasters.[33]

[33] Appendix Figure A.9 presents an alternative test of the intensity effect, showing that customers' output growth declines as the proportion of affected inputs or suppliers increases.

The substitution effect. To test the substitution effect, we examine whether customer firms shift input purchases away from shocked suppliers toward unaffected ones. Following a disruption to one supplier within a 6-digit NAICS industry, we test whether customer firms increase expenditures on inputs from unaffected suppliers in the same industry. Given that suppliers within narrowly defined industries produce similar, easily substitutable inputs, we expect firms to increase purchases from unaffected suppliers in response to shocks. To test this formally, we run the following regression:

$$\Delta \log x_{iI,t}^{jJ} = \alpha + \tau_t + \eta_{iI} + \kappa^J + \sum_{k=-4}^{10} \kappa_k \cdot \mathbb{I}[\text{Shock hits } iI]_{t-k} + \sum_{k=-4}^{10} \beta_k \cdot \mathbb{I}[\text{Shock hits } jJ]_{iI,t-k}$$
$$+ \sum_{k=-4}^{10} \gamma_k \cdot \mathbb{I}[\text{Shock hits some firm(s) in } J, \text{ but not } jJ]_{iI,t-k} + \lambda' \mathbf{X}_{iI,t}^{jJ} + \varepsilon_{iI,t}^{jJ}, \quad (13)$$

where $\Delta \log x_{iI,t}^{jJ}$ is the growth of customer firm iI's real input purchases from supplier j in industry J between t and $t-4$. $\mathbb{I}[\textit{Shock hits } jJ]_{t-k}$ is a dummy that takes the value one if supplier jJ of customer iI was hit by a shock in quarter $t-k$. $\mathbb{I}[\textit{Shock hits some firm(s) in } J, \textit{ but not } jJ]_{iI,t-k}$ is a dummy that takes the value one if iI's supplier jJ is not hit by a disaster *but* there exists at least one *other* supplier of iI (from the same 6-digit NAICS industry, J) that was hit by a disaster in quarter $t-k$. As above, we also control for $\mathbb{I}[\text{Shock hits } iI]_{t-k}$ 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 (13) includes all additional controls in Equation (7) as well as suppliers' age, number of employees and supplier industry fixed effects.

The results are shown in Figure 4. The orange line represents the impact on input purchases from disaster-affected suppliers (the β_k's in Equation 13) for up to 10 quarters following a disaster. The blue line shows the change in input purchases from unaffected suppliers over the same horizon (γ_k's in Equation 13). 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 multisourcing firms in Figure 2, suggesting that the propagation of supply shocks is substantially mitigated when customer firms multisource 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

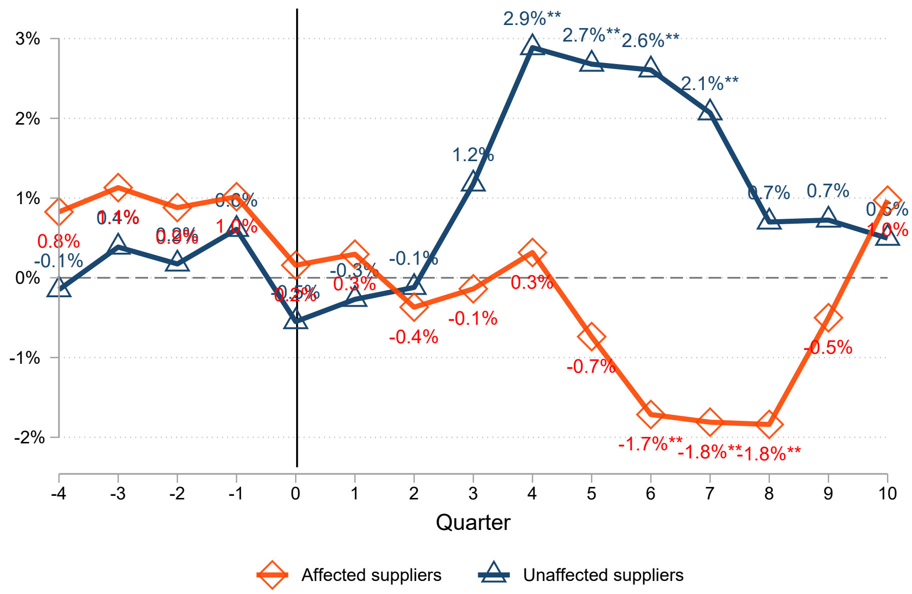

Figure 4: Substitution Towards Unaffected Suppliers

Note: This figure shows estimates relating to regression specification (13). The orange 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.

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 in Figure 4 show that multisourcing customers temporarily substitute input purchases from affected to unaffected suppliers from the same industry, where input purchases return to normal after roughly two years.

3.6 Ruling out alternative explanations and other robustness checks

In this section, we address some important concerns relating to the results discussed above. Our broad objective is to highlight that the attenuation effects estimated in Figure 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) Are our estimates biased by staggered treatments? 3) Is firms' input-sourcing behavior independent of disasters? 4) Are supplier-customer links endogenous to disasters? 5) Are suppliers of multisourcing customers less affected by disasters? 6) Is multisourcing correlated with suppliers' input-specificity?

How does the customer reporting threshold affect our estimates? A possible concern is that the 10% reporting threshold may induce measurement error in our multisourcing measures, as we do not observe suppliers that fall below this threshold. However, this is unlikely to affect our findings for two reasons. First, using the same data, Atalay et al. (2011) show that the fraction of customer-supplier links that are missed because of the 10% rule is similar for customers with many or few observed suppliers. Hence, our multisourcing measure $\mathcal{M}_{iI,t}^{\text{Count}}$ correctly *ranks* firms by their level of multisourcing, even though there are unobserved suppliers. The results in Figure 2 based on the supplier count measure are similar to those using firms' HHIs, which gives us confidence that both measures accurately capture firms' multisourcing behavior.

Second, and more importantly, any remaining measurement error in the multisourcing measures would likely bias our estimates *against* finding an effect of multisourcing on shock propagation. This is because the attenuation of shocks by some firms that truly multisource intermediate inputs will be incorrectly attributed to the group of non-multisourcing firms, and vice versa. Overall, such measurement error will dilute the difference in sales growth between the two groups of firms.[34] For this reason, we view our estimates in Figure 2 as a lower bound of the attenuation effects of multisourcing.

Relatedly, given the 10% reporting threshold, one may be concerned that multisourcing firms are large firms buying inputs from small suppliers, over which they may have greater bargaining power. If affected suppliers first serve their most important customers, the attenuation effects we estimate in Figure 2 may actually reflect the benefit of having more bargaining power over suppliers and not the benefits of multisourcing. In Appendix Table A.3, we augment Equation (7) to control for firms' level of bargaining power using the measure defined in Ahern (2012). Specifically, we measure a customer firm's bargaining power over each supplier by first calculating the ratio of the customer's purchases from the supplier to the supplier's total sales. We then compute the firm's bargaining power at quarter t as a weighted average of this ratio across all suppliers, with the weights given by the customer's purchases from each supplier as a share of the customer's total purchases in that quarter. 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 multisourcing on shock propagation remains when we control for firms' bargaining power.

Are our estimates biased by staggered treatments? Another concern arises from a recent literature showing that difference-in-differences estimates can be biased when treatment timing varies across units (e.g., de Chaisemartin and D'Haultfœuille, 2020; Sun and Abra-

[34] To demonstrate that measurement error leads to an underestimation of the attenuation effects of multisourcing, we re-run specification (7) with customers randomly assigned as multisourcing firms. Appendix Table A.2 presents the results, showing no effect of multisourcing on shock propagation across all specifications when firms are randomly classified as multisourcers.

ham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Borusyak et al., 2024). In our context, this bias could arise from comparing firms affected by supplier shocks with firms impacted in earlier periods. To address this, we follow Wooldridge (2021) by estimating event-specific effects on the sales growth of multi- and non-multisourcing customers, avoiding "forbidden comparisons" with earlier-treated firms (Goodman-Bacon, 2021). Specifically, we estimate

$$\begin{aligned}\Delta \log Q_{iI,t} = \alpha + \beta^e \cdot \text{Event}^e_{iI,t} + \kappa^e \cdot \text{Event}^e_{iI,t} \times \mathbb{I}[iI \text{ Multisources}]_t \\ + \delta \cdot \mathbb{I}[iI \text{ Multisources}]_t + \left(\text{Event}^e_{iI,t} \cdot \dot{\mathbf{X}}^e_{iI,t}\right)' \boldsymbol{\gamma}^e + \mathbf{X}'_{iI,t}\boldsymbol{\lambda}_t + \tau_t + \eta_{iI} + \varepsilon_{iI,t}, \quad (14)\end{aligned}$$

where $Event^e_{iI,t}$ is an indicator that equals one if firm iI in quarter t is first treated in quarter $t = e$, and zero otherwise. Here, *treatment* refers to being hit by a supplier shock four quarters earlier. For example, there is a cohort of customers who take a value of one in October 2013 because i) their suppliers were affected by Hurricane Sandy in October 2012 and ii) the suppliers of these customers had never experienced a natural disaster before Hurricane Sandy. These customer firms drop out of the sample after October 2013, avoiding comparisons with other customer firms that are hit with supplier shocks later in the sample. $\mathbb{I}[iI\ Multisources]_t$ denotes one of the two multisourcing indicators defined in Section 3.3, and $\mathbf{X}_{iI,t}$ is a vector of controls interacted with year-quarter fixed effects, including tercile dummies for firm age, number of employees, number of suppliers, total assets, and return on assets. $\mathbf{X}_{iI,t}$ also includes dummy variables indicating whether a firm was directly hit by a natural disaster four quarters earlier and fiscal quarter dummies. $\dot{\mathbf{X}}^e_{iI,t}$ represents the same controls, centered by their cohort-specific means.[35] Finally, τ_t and η_{iI} are year-quarter and firm fixed effects, respectively. Since the event dummies are defined with a four-quarter lag, our estimates capture the effect on customer firms' sales growth after one year.[36] We run separate regressions for each multisourcing measure and estimate cohort-specific treatment effects for multi- and non-multisourcing firms: $(\hat{\beta}^e + \hat{\kappa}^e)$ and $(\hat{\beta}^e)$, respectively. Finally, we aggregate the treatment effects across cohorts using cohort-size weights.[37]

The results are presented in Appendix Table A.4. The first two columns relate to the HHI multisourcing measure (Equation 4), while columns 3 and 4 correspond to the sup-

[35] Centering the covariates in the interaction term around their cohort-specific means allows our estimates to be interpreted as the average treatment effect for multi- and non-multisourcing firms within cohort e.

[36] While we focus on the fourth lag where the impact of the supply shock is most pronounced, our results are consistent with the baseline (Figure 2) if we define the $Event^e_{iI,t}$ dummy such that the treatment occurs at different leads or lags.

[37] The weight for each cohort is the number of customers treated in event e, as a share of the total number of treated customer firms in the sample.

plier count measure (Equation 6). Each specification gives results that are near identical to those in Figure 2, suggesting that issues raised by the recent staggered difference-in-differences literature are unlikely to bias our results.

Is multisourcing independent of disasters? If firms begin multisourcing inputs only after a disaster affects an existing supplier, the estimates in Figure 2 may overstate the attenuation effects of multisourcing. This is because what appears to be shock mitigation due to multisourcing could, in fact, be driven by other firm characteristics, such as better preparedness for supply disruptions or maintaining higher inventory levels. To test whether multisourcing is independent of disasters, we run the following regression

$$\begin{aligned}\mathcal{M}_{iI,t} &= \alpha + \beta \cdot \text{\# Supplier Disruptions in Past Five Years}_{iI,t} \\ &+ \gamma \cdot \text{\# Disasters in Past Five Years}_{iI,t} + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t},\end{aligned} \tag{15}$$

where $\mathcal{M}_{iI,t}$ corresponds to the multisourcing measures (4) and (6). We regress each multisourcing measure on the number of disruptions experienced by i) the firm itself and ii) its suppliers, over the past five years. In addition, we also include the same controls $\mathbf{X}_{iI,t}$ as specification (7) as well as time τ_t and firm η_{iI} fixed effects.

The results relating to regression (15) are presented in Appendix Table A.5. First, we find firms' level of multisourcing to be orthogonal to the number of disasters the firm *itself* experienced in the past five years. The estimated coefficient on the number of disasters directly striking customer firms is near zero for each multisourcing measure. Crucially, the number of supplier disruptions in the previous five years also does not predict firms' level of multisourcing across each of our measures. The estimated coefficients on the # *Supplier Disruptions in Past Five Years* are statistically insignificant and near-zero across each specification.[38]

The results in Appendix Table A.5 suggest that firms' multisourcing behavior is orthogonal to natural disasters. This finding is not inconsistent with the recent literature on firms' responses to climate risks (e.g., Balboni et al., 2024; Blaum et al., 2024; Castro-Vincenzi et al., 2024) which shows that firms whose suppliers are exposed to *systematic and predictable* weather events are more likely to diversify their supply base. Shocks in our sample are short-lived (<30 days) and represent one-off disasters (e.g., hurricanes). It is possible that firms do not insure against such shocks, opting instead to make systematic and permanent changes to their input sourcing decisions only in response to more persistent weather conditions or other routine sources of supply variability.

[38]Regressions involving the continuous multisourcing measures assess whether disasters affect the level of multisourcing at the intensive margin. We also find multisourcing to be independent of disasters along the extensive margin (where the outcome variables are the multisourcing indicators). Results are available upon request.

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 Appendix Figure A.4 and Figure 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

$$\text{\# New Links Created}_{county,t} = \alpha + \beta \cdot \text{\# of Disasters}_{county,(t-5,\ t)} + \tau_t + \gamma_{county} + \varepsilon_{county,t} \quad (16)$$

$$\text{\# Old Links Destroyed}_{county,t} = \alpha + \beta \cdot \text{\# of Disasters}_{county,(t-5,\ t)} + \tau_t + \gamma_{county} + \varepsilon_{county,t}. \quad (17)$$

Equations (16) and (17) have a unit of observation as a county-year. Equation (16) 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 (17) 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 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.[39] 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 seemingly insensitive to unanticipated shocks, as in Kinnan et al. (2024).[40] The sunk costs involved in the search for and selection of suppliers can further discourage customers from reacting to temporary and unpredictable supply disturbances (Antrás et al., 2017; Bernard et al., 2019).

Are suppliers of multisourcing customers less affected by disasters? It is important to consider whether natural disasters impact suppliers of multi- and non-multisourcing customers differently. For example, are suppliers of non-multisourcing firms systematically worse hit by natural disasters? Alternatively, do suppliers of multisourcing customers deal with natural disasters more effectively? If the answer to the above questions is yes,

[39]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).

[40]Relatedly, Martin et al. (2023) find that firms' supply relationships are sticky during periods of high uncertainty.

then the observed attenuation effects of multisourcing may be due to the heterogeneous impact of disasters on suppliers of multi- and non-multisourcing firms. Appendix Table A.7 investigates this proposition, displaying estimates for the marginal effect of supplying to a 'multisourcing firm' on sales growth when hit by a disaster.

The table shows regression results over the supplier sample. We create a dummy variable that takes the value one if at least one of the firm's customers is identified as a multisourcer at time t and zero otherwise (based on the HHI and supplier count approaches). We regress suppliers' sales growth on i) an indicator that takes a value one if a natural disaster hits the firm in any of the previous two years and ii) the interaction of this disaster dummy with the multisourcing customer dummy. Under both multisourcing measures, we find that suppliers to both multi- and non-multisourcing customers experience nearly identical changes in sales growth when struck by a natural disaster (first row). Moreover, the table shows that the impact of a natural disaster on firms' sales growth (second row) is consistent with the estimates displayed in Appendix Figure A.4. Overall, the impact of major natural disasters on firm sales growth appears to be orthogonal to the level of multisourcing of the affected firms' customers.

Is multisourcing correlated with suppliers' input-specificity? Barrot and Sauvagnat (2016) find disaster-affected suppliers impose substantial output losses on their customers when the suppliers produce *specific inputs*. Barrot and Sauvagnat consider a supplier as specific if i) its industry share of differentiated (non-homogeneous) 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 3-4pp if a natural disaster hits a specific supplier.

A valid concern is whether there is any systematic correlation between customers' multisourcing behavior and suppliers' input specificity. If multisourcing customers have non-specific suppliers in general, then the attenuation of supply shocks shown in Figure 2 may not be attributable to multisourcing but to the absence of specific inputs for such customers. In Appendix Table A.8, we check how the results reported in Figure 2 change if we control for input specificity.[41] We focus on the fourth lag, where the propagation of shocks to customer firms is greatest, to keep the model parsimonious. We find similar results at other lags. Appendix Table A.8 reports different versions of Equation (7) using the customer sample but with an additional indicator $\mathbb{I}[\textit{Shock hits specific supplier } jJ]_{iI,t-4}$ that takes the value one if, for a customer firm iI, at least one specific supplier jJ was

[41] We thank Julien Sauvagnat for sharing data on the three measures of input specificity.

affected by a natural disaster four quarters back. In addition, we control for an indicator $\mathbb{I}[\textit{Specific supplier}]_{iI,t-4}$ that takes the value one if firm iI had at least one specific supplier at $t-4$. In Appendix Table A.8, we define supplier specificity based on patents. The results are qualitatively the same when we use Rauch (1999) and R&D as measures of input specificity.[42]

Appendix Table A.8 shows that: i) multisourcing firms attenuate supply shocks by approximately 3-4pp (row 1), ii) when a specific supplier is hit with a disaster, its customers experience an additional 3pp decline in sales growth after four quarters (row 2), and iii) customers' sales growth declines by approximately 4pp four quarters after a supplier shock (row 3), consistent with Figure 2. Overall, the results suggest that both multisourcing and input specificity are crucial in influencing how shocks propagate from suppliers to customers. While suppliers' input specificity amplifies the transmission, customers' level of multisourcing mitigates it.

4 Conceptual framework and quantitative results

In this section, we interpret the empirical results from Section 3 through the lens of a canonical production network model. We show that multisourcing attenuates firm-level supply shocks. Consistent with the mechanisms discussed above, both intensity and substitution effects explain this result. Finally, we use the model to quantitatively assess the aggregate implications of firm-level multisourcing in response to idiosyncratic microeconomic shocks, comparing an economy in which firms multisource from many suppliers to one in which firms single-source inputs for production.

Preliminaries. Consider a static economy with two types of agents: a representative household and heterogeneous firms. There is a set of narrowly defined industries N. Each industry is populated by a set of firms N_J. N and N_J also denote the cardinality of the sets of industries and firms within industry J, respectively. As above, we denote a firm j in industry J as jJ. The output of firms within an industry is near-identical. Firms in each industry J set prices equal to marginal cost times an exogenous industry-level markup μ_J. The advantage of this approach is that we can i) derive comparative static results without committing to any specific theory of wedge determination (Baqaee and Farhi, 2020), and ii) allow market power to vary at the industry level. For example, industries with fewer suppliers can charge a higher markup. Firms' output can be consumed as intermediate inputs by other firms in any industry or by the representative household as final consumption.

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

4.1 Production

Firm i in industry I produces output according to a Cobb-Douglas production function,

$$Q_{iI} = (z_{iI} k_{iI})^{\alpha} M_{iI}^{1-\alpha}, \tag{18}$$

where Q_{iI} is gross output, k_{iI} is capital, M_{iI} is a bundle of intermediate inputs, α is the capital share, and z_{iI} is a capital-augmenting productivity shock. The intermediates good bundle is a Cobb-Douglas aggregator of industry-level intermediate goods

$$M_{iI} = \prod_{J \in N} X_{iI}^{J\ \omega_I^J},$$

where X_{iI}^J is a bundle of intermediate inputs from firms within industry J and $\omega_I^J > 0$ is a parameter governing the importance of industry J in the production of I's output, with $\sum_{J \in N} \omega_I^J = 1$ for all I. The bundle X_{iI}^J is an aggregator of firm-level intermediates

$$X_{iI}^J = \left(\sum_{j \in N_J} x_{iI}^{jJ\ \frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{19}$$

where $\rho > 1$ and x_{iI}^{jJ} is the quantity of intermediates from firm jJ used by iI.[43] The aggregator (19) captures the multisourcing behavior of firms. When multiple suppliers exist in industry J, firm $i \in N_I$ distributes its input purchases across firms within J. While it appears that all firms producing the composite good I exhibit identical sourcing behavior over input J, our framework allows for heterogeneity in multisourcing within industries. Specifically, one can always define fictitious customer and supplier sectors, I' and J', such that the number of suppliers, $N_{J'}$, differs from N_J. Firms in I and I' share the same production technologies and therefore have identical expenditure shares on inputs from J and J', respectively. Importantly, however, firms in I and I' interact with different numbers of suppliers. Consequently, the degree of multisourcing of intermediate inputs (defined below) can vary within an industry without loss of generality.

Price indexes. The industry-level price index associated with X_{iI}^J is defined as

$$P_J \equiv \left(\sum_{j \in N_J} p_{jJ}^{\ 1-\rho} \right)^{\frac{1}{1-\rho}},$$

where p_{jJ} is the price of good j in industry J. Similarly, the price index associated with M_{iI} is defined as

[43] When $\rho \to \infty$, goods within industry J are perfect substitutes and there is no product differentiation.

$$\mathcal{P}_I \equiv \prod_{J\in N} \omega_I^{J^{-\omega_I^J}} P_J^{\omega_I^J},$$

where $\mathcal{P}_I$ is the price index for intermediate goods consumed by firms in industry I.

Shocks. We model supply chain disruptions as capital-augmenting productivity shocks, $d\log z_{iI} \leq 0$, to align with our empirical analysis in Section 3, where we identify firm-level shocks with the occurrence of major natural disasters in the US. As in Carvalho et al. (2021), this approach captures the idea that natural disasters reduce the operable capital of disaster-affected firms.

Cost minimization and market-clearing. Each firm solves the cost minimzation problem:

$$\min_{\substack{k_{iI}, x_{iI}^{jJ} \\ \{j\in N_J\}\forall J}} \quad rk_{iI} + \sum_{J\in N}\sum_{j\in N_J} p_{jJ} x_{iI}^{jJ} \qquad \text{s.t.} \qquad (18),$$

where r is the rental price of capital, k_{iI} is firm iI's capital input, and x_{iI}^{jJ} is the quantity consumed by iI of good jJ.[44] The only distortions in the economy are industry-level markups μ_I. Like in Liu (2019) and Bigio and La'O (2020), we assume payments from distortions leave the economy.[45]

Goods market-clearing is then described by

$$Q_{iI} = C_{iI} + h_{iI} + \sum_{J\in N}\sum_{j\in N_J} x_{jJ}^{iI}, \quad \text{for all} \quad i \in N_I \ \& \ I \in N$$

which states that iI's output (Q_{iI}) can either be consumed as a final good by the household (C_{iI}), as intermediate goods by other firms (x_{jJ}^{iI}), or thrown out (h_{iI}). Similarly, the capital market-clearing condition is given by $\sum_{J\in N}\sum_{j\in N_J} k_{jJ} = K$, where K represents the aggregate, inelastically supplied capital stock.

4.2 Household preferences

There is a representative household that consumes final goods and derives income by supplying capital inelastically to firms. The household has preferences over aggregate consumption, or, equivalently in this setting, real GDP $u(Y)$, where[46]

[44] We take capital as the numeraire, so $r = 1$.

[45] We denote the quantity of good iI that is removed from the economy due to distortions as $h_{iI} = \left(1 - \frac{1}{\mu_I}\right) Q_{iI}$. This is done only for analytical tractability, and the key insights of the model continue to hold if rents from distortions are rebated to the household.

[46] The utility function $u(\cdot)$ is twice continuously differentiable and concave.

$$Y = \prod_{J \in N} \prod_{j \in N_J} C_{jJ}^{\theta}. \tag{20}$$

While equation (20) assumes all goods are equally important in final demand (i.e., θ is a constant), our theoretical results do not depend on this assumption.

Household problem. The household's optimization problem is given by

$$\max_{\substack{C_{jJ} \\ \{j \in N_J\} \forall J}} u(Y) \quad \text{s.t.} \quad rK = \sum_{J \in N} \sum_{j \in N_J} p_{jJ} C_{jJ},$$

where $\sum_{J \in N} \sum_{j \in N_J} p_{jJ} C_{jJ}$ is nominal GDP.

Equilibrium. A general equilibrium is a collection of goods prices $\{p_{iI}\}$, rental price r, intermediate inputs $\{x_{iI}^{jJ}\}$, outputs $\{Q_{iI}\}$, final demands $\{C_{iI}\}$, and capital inputs $\{k_{iI}\}$, such that given productivities $\{z_{iI}\}$ and markups $\{\mu_I\}$, each firm minimizes its costs subject to its technology, the representative household chooses consumption to maximize utility subject to its budget constraint, and markets for goods and capital clear.

4.3 Input-output notation and measuring multisourcing

We introduce some input-output notation that plays a central role in our theoretical results. In the terminology of Baqaee and Farhi (2020), all objects in this subsection are "cost-based", meaning they are defined in terms of firms' expenditures as opposed to revenues. It is useful to note that firms' total costs can be expressed as $TC_{iI} = \mu_I^{-1} p_{iI} Q_{iI}$, where $\mu_I^{-1} p_{iI}$ is iI's marginal cost.

Input-output and Leontief inverse matrices. We begin by specifying the economy's firm-level input-output network. Let $\mathbf{\Omega}$ be an $\sum_{J \in N} N_J \times \sum_{J \in N} N_J$ block input-output matrix with iI, jJ^{th} element given by[47]

$$\Omega_{iI}^{jJ} = \mu_I \frac{p_{jJ} x_{iI}^{jJ}}{p_{iI} Q_{iI}}.$$

The input-output parameter Ω_{iI}^{jJ} equals the expenditure by firm iI on intermediate inputs from firm jJ as a share of iI's total costs. It is a measure of firm iI's direct reliance on intermediates from jJ.

[47] Each block of $\mathbf{\Omega}$ summarizes the input-output linkages between two industries. Formally,

$$\mathbf{\Omega} = \begin{bmatrix} \mathbf{\Omega}_1^1 & \mathbf{\Omega}_1^2 & \cdots & \mathbf{\Omega}_1^N \\ \mathbf{\Omega}_2^1 & \mathbf{\Omega}_2^2 & \cdots & \mathbf{\Omega}_2^N \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{\Omega}_N^1 & \mathbf{\Omega}_N^2 & \cdots & \mathbf{\Omega}_N^N \end{bmatrix} \quad \text{and} \quad \mathbf{\Omega}_I^J = \begin{bmatrix} \Omega_{1I}^{1J} & \Omega_{1I}^{2J} & \cdots & \Omega_{1I}^{N_J,J} \\ \Omega_{2I}^{1J} & \Omega_{2I}^{2J} & \cdots & \Omega_{2I}^{N_J,J} \\ \vdots & \vdots & \ddots & \vdots \\ \Omega_{N_I,I}^{1J} & \Omega_{N_I,I}^{2J} & \cdots & \Omega_{N_I,I}^{N_J,J} \end{bmatrix},$$

where $\mathbf{\Omega}_I^J$ contains information on expenditures by firms in industry I on intermediates from industry J.

Associated with $\mathbf{\Omega}$ is the $\sum_{J\in N} N_J \times \sum_{J\in N} N_J$ Leontief inverse matrix

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

where $\mathbf{I}$ is the $\sum_{J\in N} N_J \times \sum_{J\in N} N_J$ identity matrix. The Leontief inverse captures all direct and indirect linkages between firms in the economy. $\mathbf{\Psi}$ is also a block matrix where $\mathbf{\Psi}_I^J$ contains all direct and indirect paths between firms in industries J and I. We denote the iI, jJ^{th} element of $\mathbf{\Psi}$ by ψ_{iI}^{jJ}.

Intermediate input shares. We define an $\sum_{J\in N} N_J \times \sum_{J\in N} N_J$ matrix of firm-level intermediate input expenditure shares $\mathbf{\Phi}$, with iI, jJ^{th} element given by

$$\Phi_{iI}^{jJ} = \frac{p_{jJ} x_{iI}^{jJ}}{P_J X_{iI}^J},$$

where Φ_{iI}^{jJ} is firm iI's expenditure on intermediates from firm jJ as a share of iI's total expenditure on inputs from industry J. Below, we use the input shares $\mathbf{\Phi}$ to measure firms' level of multisourcing.

We also define $N \times 1$ vectors of industry-level input expenditure shares $\mathbf{\Theta}_{iI}$, with J^{th} element given by

$$\Theta_{iI}^J = \frac{P_J X_{iI}^J}{\mathcal{P}_I M_{iI}},$$

which is firm iI's expenditure on intermediate inputs from industry J, as a share of iI's total intermediate input expenditure. Each firm iI has a corresponding vector $\mathbf{\Theta}_{iI}$.

Domar weights. Finally, we define an $\sum_{J\in N} N_J \times 1$ vector of Domar weights $\boldsymbol{\lambda}$, with iI^{th} element given by

$$\lambda_{iI} = \frac{1}{\mu_I} \frac{p_{iI} Q_{iI}}{\text{GDP}} = \theta \sum_{J\in N} \sum_{j\in N_j} \psi_{jJ}^{iI}. \tag{21}$$

The Domar weight λ_{iI} is defined as firm iI's total cost as a share of nominal GDP. The second equality in (21) highlights that λ_{iI} also measures the direct and indirect exposure of final demand to firm iI in equilibrium. Since each good has an equal share in final demand (θ), λ_{iI} is also equal to the average weighted path between firm iI and all other firms in the economy.[48]

Measuring multisourcing. Similar to Section 3, we define HHIs that measure the degree of concentration of a firm's intermediate input purchases across suppliers from each industry. The extent to which firm iI's intermediate input purchases are dispersed across

[48]Equation (21) is derived from the goods market-clearing condition for iI. Domar weights are given by $\lambda_{iI} = \theta + \sum_{J\in N} \sum_{j\in N_J} \Omega_{jJ}^{iI} \lambda_{jJ}$. Rearranging this equation implies $\boldsymbol{\lambda}' = \theta \mathbf{1}' \mathbf{\Psi}$.

suppliers from industry J is given by

$$\mathcal{M}_{iI}^{J} = \sum_{j \in N_J} \left(\Phi_{iI}^{jJ}\right)^2, \tag{22}$$

where $0 < \mathcal{M}_{iI}^{J} \leq 1$ is a HHI of input shares $\{\Phi_{iI}^{jJ}\}_{j \in N_J}$. The Herfindahl $\mathcal{M}_{iI}^{J}$ takes a lower value if firm iI sources intermediates from many suppliers in industry J in less concentrated proportions. If $\mathcal{M}_{iI}^{J} = 1$, then iI single-sources input J (i.e., firm iI has only one supplier from industry J). Since firm iI can purchase inputs from each of the N industries, there is a Herfindahl defined for each supplier industry, $\{\mathcal{M}_{iI}^{1}, ..., \mathcal{M}_{iI}^{N}\}$. Below, we characterize changes in output at both the microeconomic and macroeconomic levels as a function of the HHIs at the initial equilibrium. We derive our comparative static results around the steady state (as in Baqaee, 2018 and Carvalho et al., 2021), defined as the point at which productivities may vary across industries but are equal across firms within each industry. This formulation also encapsulates our second measure of multisourcing from Section 3, as, in steady state, Equation (22) corresponds to the inverse of the number of suppliers in sector J that firm iI sources from.

Equation (22) highlights that as iI distributes its input purchases across more suppliers from industry J, the HHI approaches zero ($\mathcal{M}_{iI}^{J} \to 0$). It is important to note that $\mathcal{M}_{iI}^{J}$ responds endogenously to shocks whenever $\mathcal{M}_{iI}^{J} < 1$ at the initial equilibrium, as customer firms substitute away from the shocked supplier to other unaffected suppliers in industry J. In the next subsection, we highlight how the substitution behavior of customer firms mitigates the decline in their output following a shock to a supplier.

4.4 Comparative statics and quantitative results

In this section, we derive our comparative static results. We consider the micro- and macroeconomic effects of a negative capital-augmenting productivity shock to firm k in industry K, $\Delta \log z_{kK} < 0$, which we interpret as an exogenous production disruption to kK. We express our results in terms of the customer firm's (iI's) level of multisourcing from the supplier industry (K), i.e., $\mathcal{M}_{iI}^{K}$, highlighting how multisourcing attenuates supply shocks and maintaining consistency with our empirical results in Section 3. All results in this section can equivalently be expressed in terms of input-output parameters, as in other papers in the production networks literature (e.g., Acemoglu et al., 2012; Liu, 2019; Bigio and La'O, 2020). The proofs of all results discussed below are presented in Appendix C.

Customers' output. Our first result characterizes the change in the gross output of firm iI in response to a production disruption to its supplier kK, up to a second-order of approximation:

$$\Delta \log Q_{iI} \approx \alpha \times \underbrace{\beta_I^K \mathcal{M}_{iI}^K}_{\text{Intensity effect}} \times \left(\Delta \log z_{kK} + \frac{\alpha}{2} \underbrace{(\rho - 1)\left(1 - \mathcal{M}_{iI}^K\right)}_{\text{Substitution effect}} (\Delta \log z_{kK})^2 \right), \tag{23}$$

where β_I^K is a parameter that measures the direct and indirect dependence of industry I on inputs from industry K.[49] Equation (23) highlights the distinct mechanisms, as discussed in Section 3, through which multisourcing firms attenuate supply shocks. First, $\beta_I^K \mathcal{M}_{iI}^K$ corresponds to the *intensity effect* discussed in Section 3.5. Intuitively, a negative shock to supplier kK reduces customer iI's output by a smaller amount when $\mathcal{M}_{iI}^K$ is lower. When $\mathcal{M}_{iI}^K$ is low, firm iI sources inputs from industry K in less concentrated proportions, meaning that a shock to any one supplier in industry K has a smaller impact on output since only a small fraction of iI's inputs from K are affected. The propagation of the shock increases with iI's direct and indirect dependence on inputs from industry K, measured by β_I^K.

Second, the term $(\rho - 1)\left(1 - \mathcal{M}_{iI}^K\right)$ in Equation (23) reflects the *substitution effect*, which highlights that firm iI's ability to substitute toward unaffected suppliers within industry K depends on the *interaction* between its level of multisourcing from industry K and the elasticity of substitution between inputs from different firms in K. Since $\rho > 1$, the substitution effect is always positive, indicating that the substitution behavior of multisourcing firms attenuates the impact of negative supplier shocks. Intuitively, when firm iI multisources inputs from industry K ($\mathcal{M}_{iI}^K < 1$), a negative shock to supplier kK is mitigated because iI substitutes with other suppliers in industry K that produce similar goods. Conversely, if iI single-sources inputs from K ($\mathcal{M}_{iI}^K = 1$), the second-order effect is zero because iI has no alternative suppliers within industry K to substitute. The substitution effect increases with the elasticity of substitution, ρ, and as $\mathcal{M}_{iI}^K \to 0$, but approaches zero in the Cobb-Douglas ($\rho = 1$) and single-sourcing ($\mathcal{M}_{iI}^K = 1$) limits.

The intuition behind Equation (23) is illustrated in Figure 5. The figure plots the change in output of a customer firm iI ($\Delta \log Q_{iI}$) in response to a 50% negative capital-augmenting shock to a supplier kK on the vertical axis, against the multisourcing HHI $\mathcal{M}_{iI}^K$ on the horizontal axis. The dashed blue line represents the change in output without the substitution effect, while the solid blue line depicts the total change in output, including the substitution effect.[50]

The red line shows that $\Delta \log Q_{iI} = -6\%$ when the firm single-sources inputs from industry K. In this case, the decline in output is largest since firm iI is fully exposed to the

[49] Formally, $\beta_I^K \equiv (1-\alpha)\omega_I^K + (1-\alpha)^2 \sum_{M \in N} \omega_I^M \omega_M^K + \ldots$

[50] For the purposes of the illustration, we set $\alpha = 0.4$, $\beta_I^K = 0.3$, and $\rho = 12$.

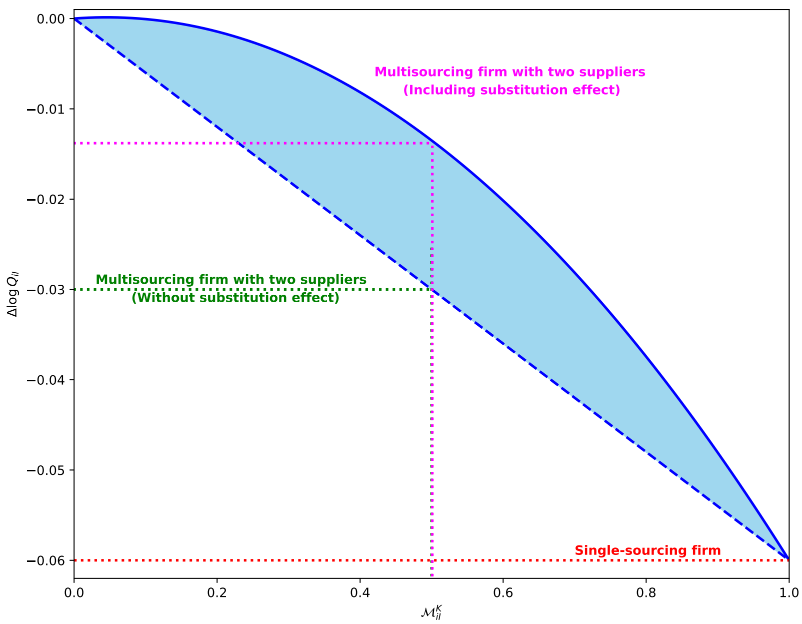

Figure 5: Multisourcing and the Attenuation of Supply Chain Disruptions

Note: The figure plots the change in output of a customer firm iI in response to a negative capital-augmenting shock to a supplier kK (vertical axis) against the multisourcing HHI $\mathcal{M}_{iI}^K$ (horizontal axis). The dashed blue line represents the change in output without the substitution effect, while the solid blue line depicts the change in output inclusive of the substitution effect as shown in Equation (23).

shock and cannot substitute toward other suppliers.[51] However, when customer iI multisources inputs, the decline in their output in response to a supplier shock is substantially mitigated. The green line shows the change in output (absent the substitution effect) of a multisourcing firm with two suppliers, where $\mathcal{M}_{iI}^K = 1/2$. Without the substitution effect, firm iI's output declines by 3% because only 50% of its inputs from industry K are affected by the shock. Accounting for the substitution effect (magenta line), the decline in output is even smaller. In this case, as firm iI substitutes away from firm kK, it avoids a severe production shortfall, reducing the output decline to just 1.3%.

Intermediate inputs. We now turn to our second result, which rationalizes the results discussed in Figure 4. That is, we discuss how the customer firm's (iI's) use of intermediate inputs changes when a firm in supplier industry K is hit by a supply shock. In response to a shock to supplier kK, customer iI increases its consumption of intermediate inputs from an unaffected supplier mK by

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = \underbrace{\alpha\psi_{mK}^{kK}}_{\text{Price effect}} \underbrace{-\alpha(\rho-1)\mathcal{M}_{iI}^K,}_{\text{Substitution}} \tag{24}$$

[51]The first-order approximation $\Delta\log Q_{iI} \approx \alpha\beta_I^K \mathcal{M}_{iI}^K \Delta\log z_{kK}$ is globally accurate if iI single-sources inputs from industry K.

and iI substitutes away from the shocked firm kK, according to

$$\frac{d\log x_{iI}^{kK}}{d\log z_{kK}} = \underbrace{\alpha\psi_{kK}^{kK}}_{\text{Price effect}} + \underbrace{\alpha\left(\rho-1\right)\left(1-\mathcal{M}_{iI}^{K}\right)}_{\text{Substitution}}. \tag{25}$$

The substitution effect in Equation (24) highlights that in response to a negative shock to supplier kK, customer iI's use of intermediates from an unaffected supplier mK increases whenever iI multisources inputs from industry K.[52] Substitution towards mK *decreases* with iI's HHI because, with a greater number of suppliers in industry K, the increase in intermediate consumption is evenly distributed across all unaffected suppliers. If there are few unaffected suppliers, firm iI increases its consumption of intermediates from those few suppliers by more. The price effect in Equation (24) captures how the extent of substitution is attenuated if mk's price increases in response to the shock. Firm mK's price increases if it is a direct or indirect customer of firm kK, implying $\psi_{mK}^{kK} > 0$. In this case, the relative difference in prices between firms mK and kK is smaller than when $\psi_{mK}^{kK} = 0$. Consequently, the customer firm iI does not increase its input consumption from mK as much, and the elasticity in (24) is closer to zero.

Equation (25) characterizes the elasticity of customer iI's use of intermediates from the shocked supplier kK. Here, the substitution term shows that iI's substitution away from the shocked supplier kK increases with the elasticity of substitution and decreases with the concentration of input supplies from industry K. In the extreme cases, there is no substitution possible if kK is the only firm in industry K (i.e., $\mathcal{M}_{iI}^{K} = 1$) or if the elasticity of substitution, ρ, is equal to one. In Equation (25), the elasticity of input purchases with respect to the shock increases in the price effect. Intuitively, the shock to kK increases the price of its output (which is determined by the parameter $\psi_{kK}^{kK} \geq 1$), causing iI to demand less of kK.

Aggregate output. We now turn to our macroeconomic comparative statics. The change in aggregate output in response to a shock to supplier $k \in N_K$, up to a second-order approximation is

$$\Delta\log Y \approx \alpha\theta \underbrace{\left(1+\beta_K^K\mathcal{M}_{kK}^{K}\right)\left(\Delta\log z_{kK} + \frac{\alpha}{2}(\rho-1)(1-\mathcal{M}_{kK}^{K})\left(\Delta\log z_{kK}\right)^2\right)}_{\text{Direct effect}}$$
$$+ \underbrace{\alpha\theta\sum_{I\in N}\sum_{\substack{i\in N_I\\ i\neq k\in N_K}} \beta_I^K\mathcal{M}_{iI}^{K}\times\left(\Delta\log z_{kK} + \frac{\alpha}{2}(\rho-1)(1-\mathcal{M}_{iI}^{K})\left(\Delta\log z_{kK}\right)^2\right)}_{\text{Indirect effect}}. \tag{26}$$

[52] In the Cobb-Douglas case ($\rho = 1$), the substitution term in Equation (24) is equal to zero.

Equation (26) shows that the change in aggregate output can be decomposed into two intuitive components: the direct and indirect effects of the shock to firm kK. The direct effect reflects the reduction in final consumption of kK's output, while the indirect effect captures the decline in final consumption of kK's customers' output. Both effects comprise the intensity and substitution effects of Equation (23), and their intuition aligns with the discussion above.

For all customer firms, the intensity and substitution effects are identical to those in Equation (23). However, the intensity effect for the shocked firm takes a slightly different form, given by $\left(1+\beta_K^K \mathcal{M}_{kK}^K\right)$. The $\mathcal{M}_{kK}^K$ indicates that firm kK can source inputs from its own industry K, and the 1 relates to the direct pass-through of the shock to final consumers.

The shocked firm also has a substitution effect, which takes the usual form. The direct and indirect effects are scaled by θ, which measures the average dependence of households on final goods from firms in the economy. The macroeconomic impact of supply shocks is maximized or minimized, depending on whether all firms single source $\left(\mathcal{M}_{iI}^K \to 1\right)$ or perfectly multisource inputs $\left(\mathcal{M}_{iI}^K \to 0\right)$, respectively.

We now use Equation (26) to quantify the macroeconomic effects of multisourcing. To this end, we first use the model to estimate the elasticity of substitution between intermediates within 6-digit NAICS industries, ρ.

Model estimation. We begin by deriving an expression that allows us to estimate ρ. Up to a first-order approximation, the change in firm iK's total costs in response to capital-augmenting shocks is given by

$$\Delta \log TC_{iK} \approx (\rho - 1)\alpha \varsigma_{iK} \left(\Delta \log z_{iK} - \mathbb{E}\left[\Delta \log z_{kK}\right]\right), \tag{27}$$

where ς_{iK} is the mean intermediate expenditure on input K as a ratio of iK's total costs (formally defined in the Appendix) and $\mathbb{E}\left[\Delta \log z_{kK}\right]$ is the equal-weighted average shock in industry K.[53]

Equation (27) shows that changes in firm iK's total costs depend on the capital share α, input-output parameters (measured by ς_{iK}), and iK's capital damages relative to the average capital damages in industry K, $\left(\Delta \log z_{iK} - \mathbb{E}\left[\Delta \log z_{kK}\right]\right)$. This equation is linear in the elasticity of substitution, which allows us to estimate ρ by linear regression, provided we can measure the other variables in Equation (27). We use firm financial information from Compustat to measure ς_{iK}, data on nominal disaster damages from EM-DAT and county-level estimates of economic activity from the Bureau of Economic Analysis (BEA)

[53] See Appendix C for the proof of Equation (27).

to measure $(\Delta \log z_{iK} - \mathbb{E}[\Delta \log z_{kK}])$, and information on capital shares from the BEA's Integrated Industry-Level Production Account to calibrate the capital share α. To measure firms' total costs, we first calculate profits by subtracting depreciation expenses from firms' operating income before depreciation. Firms' total costs are then the difference between sales and accounting profits.[54] In Appendix D, we provide a detailed discussion of the data used for these measurements and the calibration of the remaining parameters in Equation (26).

The elasticity of substitution ρ is then estimated using the following specification:

$$\Delta \log TC_{iK,t+4} = \alpha + \underbrace{\beta}_{\rho-1} \cdot X_{iK,t} + \tau_t + \eta_{iK} + \varepsilon_{iK,t+4}, \tag{28}$$

where $\Delta \log TC_{iK,t+4}$ represents the year-on-year growth in firm iK's total costs four quarters ahead, while $X_{iK,t} \equiv \alpha_t \varsigma_{iK,t} \left(\Delta \log z_{iK,t} - \mathbb{E}\left[\Delta \log z_{kK,t}\right]\right)$. The coefficient β allows us to recover ρ, as $\beta = \rho - 1$. Since growth in total costs is measured four quarters ahead, our estimates can be interpreted as elasticities over a one-year horizon.

The results are presented in Table 2. We estimate ρ to range between 3.2 to 4.7, depending on the specification. In the regression with both firm and year-quarter fixed effects (column 3), we estimate $\rho = 3.3$, significant at the 1% level, which suggests a moderately high degree of substitutablility across intermediates within narrowly defined industries. We use this value as our benchmark in the macroeconomic counterfactual conducted below.

Table 2: Estimates of ρ

Controls	None	Firm FE	Firm & YQ FE
Elasticity of substitution (ρ)	4.711***	3.176***	3.329***
	[0.241]	[0.208]	[0.221]

Notes: This table presents estimates relating to Equation (28). The dependent variable in all regression is firms' year-on-year quarterly growth in total costs, after one year. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. The regressions progressively add firm and year-quarter fixed effects. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

Our elasticity estimates align well with the literature given our level of disaggregation *and* time horizon. For example, Peter and Ruane (2023) estimate an elasticity of substitution between intermediate inputs of 3.1. Relative to our case, their level of aggregation is broader (8 industries) but their time horizon is longer (7 years). Carvalho et al. (2021) use proprietary Japanese financial data to estimate a firm-level elasticity of substitution

[54] We also compute a second measure of total costs that relies on estimates of each firm's capital stock and the user cost of capital (Baqaee and Farhi, 2020). Results are robust to this alternative measure.

between intermediate inputs of 1.18 over one year. However, their elasticity measures substitutability across all goods, irrespective of supplier industries, rather than within specific industries. Broda and Weinstein (2006) estimate a median elasticity of substitution of 3.7 for seven-digit TSUSA goods, with a mean of 12.6. In our counterfactual analysis below, we test the sensitivity of our results to higher values of ρ, broadly aligning with the elasticities estimated by Broda and Weinstein (2006).

Results. We now discuss our macroeconomic results. For each quarter in our data, we estimate the average change in aggregate output in response to an idiosyncratic firm-level shock in each of the N industries. We compute the change in output for shocks ranging from -10% to -40%. We bound the effect of the shocks on GDP growth by assuming, at one extreme, that all firms are single-sourcers, while at the other, firms fully diversify their input purchases within industries.

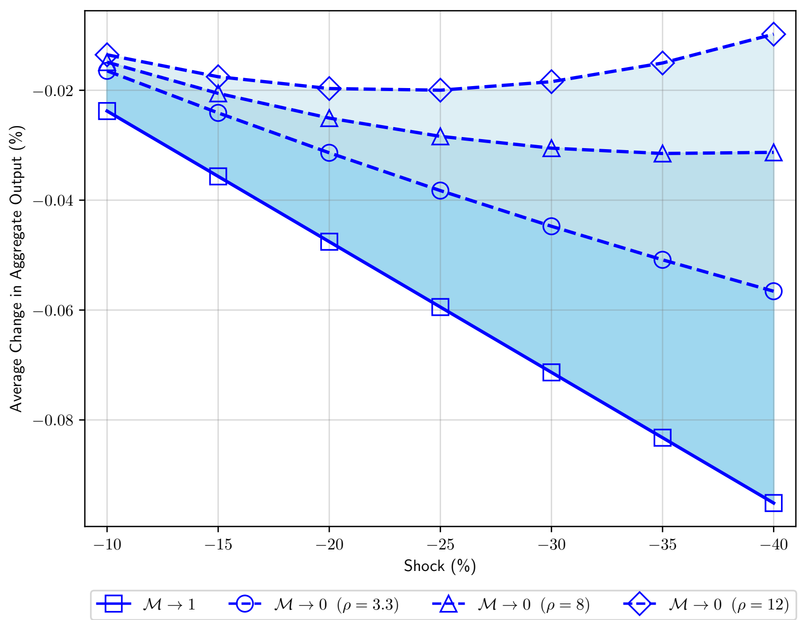

Figure 6: Macroeconomic Effects of Multisourcing

Note: This figure shows the average change in real GDP (vertical axis) in response to a firm-level capital-augmenting productivity shock (horizontal axis). The solid blue line represents the change in output when firms do not multisource intermediate inputs ($\mathcal{M} \to 1$). The dashed blue lines represent the change in aggregate output in the limit where firms are perfect multisourcers ($\mathcal{M} \to 0$). Each dashed line corresponds to a different elasticity of substitution, with $\rho = 3.3$, 8, or 12. Shaded regions represent the range of possible macroeconomic responses to the shocks.

Figure 6 shows the average change in real GDP (vertical axis) in response to an idiosyncratic firm-level capital-augmenting productivity shock (horizontal axis) for different values of $\mathcal{M}$. The solid blue line represents the change in output when firms single-source intermediate inputs ($\mathcal{M} \to 1$), illustrating the worst-case scenario of the shock.

The dashed blue lines show the change in aggregate output in the limit where firms are perfect multisourcers ($\mathcal{M} \to 0$), representing the best-case scenario. Each dashed line corresponds to a different elasticity of substitution, with $\rho = 3.3$, 8, or 12. The scenario with $\rho = 3.3$ serves as our benchmark, based on our estimates in Table 2. We also present results for higher elasticities ($\rho = 8, 12$), which are used in other studies (Baqaee and Farhi, 2020; Broda and Weinstein, 2006). Finally, shaded regions represent the range of possible macroeconomic responses to the shocks, based on the combinations of $\mathcal{M}$ and ρ.

The figure reveals three key findings. First, multisourcing substantially attenuates the macroeconomic impact of microeconomic shocks. For large (-40%) shocks, the decline in aggregate output is reduced by $\approx 40\%$ as we move from $\mathcal{M} \to 1$ to $\mathcal{M} \to 0$ (under the baseline measure of $\rho = 3.3$). Second, the macroeconomic effects are nonlinear in the size of shocks and elasticities of substitution. For large shocks and higher elasticities of substitution, the attenuation effect of multisourcing on real GDP increases non-linearly. Relative to $\mathcal{M} \to 1$, the attenuation is 40% at $\rho = 3.3$ and 90% at $\rho = 12$. Third, substitution effects are consequential at the macroeconomic level. Relative to the case of $\rho = 3.3$, the attenuation at the aggregate level approximately doubles when $\rho = 12$. Taken together, our results in Figure 6 highlight that multisourcing can have quantitatively significant macroeconomic effects.

5 Conclusion

We study the effect of multisourcing similar intermediate inputs on the propagation of shocks through supply chains. We leverage the exogenous and localized nature of natural disasters in the US between 1978 and 2017 to identify supply shocks to firms. We find that firms that multisource inputs experience reductions in sales growth that are approximately 55-70% smaller than those of non-multisourcing firms when at least one supplier is struck by a natural disaster. We causally identify the mechanisms that explain this result. Multisourcing firms are less affected by shocks because i) a smaller share of their inputs is disrupted–an *intensity effect*, and ii) they reallocate spending to unaffected suppliers producing similar inputs–a *substitution effect*.

We show that our empirical results are consistent with a canonical general equilibrium model of production networks, in which the intensity and substitution effects explain why multisourcing firms are insulated from supplier shocks. We then characterize how aggregate output responds to idiosyncratic supply shocks, demonstrating that the macroeconomic impact depends on the intensity and substitution effects of all firms in the economy. Quantitatively, we find that the attenuation of aggregate output losses increases nonlinearly with shock size. For large shocks, multisourcing similar intermediate inputs can reduce the aggregate output decline by up to 90%.

References

Acemoglu, Daron, 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.

Balboni, Clare, Johannes Boehm, and Mazhar Waseem, "Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan," July 18 2024. Unpublished manuscript.

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 Hulten's 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.

_ , Emmanuel Dhyne, Glenn Magerman, Kalina Manova, and Andreas Moxnes, "The Origins of Firm Heterogeneity: A Production Network Approach," *Journal of Political Economy*, 2022, *130* (7), 1765–1804.

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

Blaum, Joaquin, Federico Esposito, and Sebastian Heise, "Input Sourcing under Risk: Evidence from U.S. Manufacturing Firms," February 2024. Unpublished manuscript.

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.

— **and Jan Sonntag**, "Vertical Integration and Foreclosure: Evidence from Production Network Data," *Management Science*, 2023, *69* (1), 141–161.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting Event-Study Designs: Robust and Efficient Estimation," *The Review of Economic Studies*, 02 2024, p. rdae007.

Broda, Christian and David E. Weinstein, "Globalization and the Gains From Variety*," *The Quarterly Journal of Economics*, 05 2006, *121* (2), 541–585.

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

Callaway, Brantly and Pedro H.C. Sant'Anna, "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

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.

Castro-Vincenzi, Juanma, "Climate Hazards and Resilience in the Global Car Industry," Technical Report 2024. Working Paper.

— **, Gaurav Khanna, Nicolas Morales, and Nitya Pandalai-Nayar**, "Weathering the Storm: Supply Chains and Climate Risk," September 2024.

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

de Chaisemartin, Clément and Xavier D'Haultfœuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, September 2020, *110* (9), 2964â96.

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.

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.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Grassi, Basile, "IO in I-O: Competition and Volatility in Input-Output Networks," *Meet-*

ing Papers 1637, 2017.

Grossman, Gene M, Elhanan Helpman, and Alejandro Sabal, "Optimal Resilience in Multitier Supply Chains*," *The Quarterly Journal of Economics*, 08 2024, *139* (4), 2377–2425.

Grossman, Gene M., Elhanan Helpman, and Hugo Lhuillier, "Supply Chain Resilience: Should Policy Promote International Diversification or Reshoring?," *Journal of Political Economy*, 2023, *131* (12), 3462–3496.

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.

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.

Khanna, Gaurav, Nicolas Morales, and Nitya Pandalai-Nayar, "Supply Chain Resilience: Evidence from Indian Firms," November 2022.

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.

Kopytov, Alexandr, Bineet Mishra, Kristoffer Nimark, and Mathieu Taschereau-Dumouchel, "Endogenous Production Networks Under Supply Chain Uncertainty," *Econometrica*, 2024, *92* (5), 1621–1659.

Liu, Ernest, "Industrial Policies in Production Networks," *The Quarterly Journal of Economics*, 2019, *134* (4), 1883–1948.

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.

Martin, Julien, Isabelle Mejean, and Mathieu Parenti, "Relationship Stickiness, International Trade, and Economic Uncertainty," Technical Report 2023. Working paper.

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

Pankratz, Nora M C and Christoph M Schiller, "Climate Change and Adaptation in Global Supply-Chain Networks," *The Review of Financial Studies*, 12 2023, *37* (6), 1729–1777.

Patault, Bérengère and Clémence Lenoir, "Customer Capital Spillovers: Evidence from Sales Managers in International Markets," *American Economic Journal: Applied Economics*, October 2024, *16* (4), 404–43.

Peter, Alessandra and Cian Ruane, "The Aggregate Importance of Intermediate Input Substitutability," Working Paper 2023.

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.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199. Themed Issue: Treatment Effect 1.

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.

Wooldridge, Jeffrey M., "Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators," Technical Report August 2021. Working Paper.

Online Appendix to *Multisourcing and Supply Chain Disruptions*[1]

Girish Bahal Connor Jenkins Damian Lenzo

This Appendix is organized as follows. Section A provides supplementary figures and tables. Section B provides more detail on the data used in our empirical analysis. Section C provides proofs for the main theoretical results. Section D provides additional information on the data used in the quantitative exercise presented in Section 4.4 of the main text.

A Supplementary figures and tables

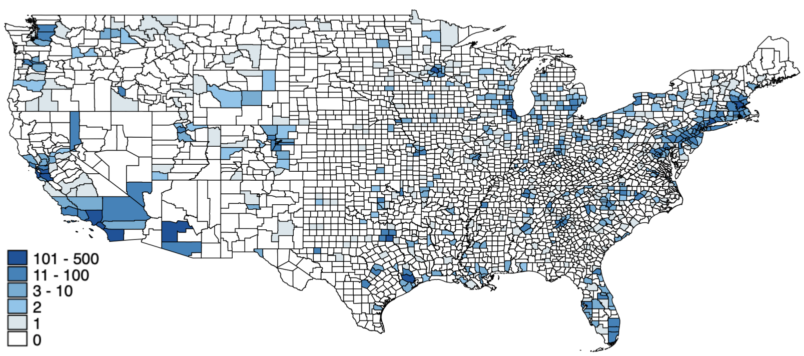

Figure A.1: Distribution of Firm Headquarters by US County (1978-2017)

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.

[1]This paper was previously circulated under the title "The Effect of Supply Base Diversification on the Propagation of Shocks". We are grateful to Toke Aidt, Enghin Atalay, Johannes Boehm, Vasco Carvalho, Arpita Chatterjee, Matthew Elliott, Apoorv Gupta, Lu Han, Michael Jetter, Bill Janeway, Callum Jones, Glenn Magerman, Julien Sauvagnat, Matthew Shapiro, Anand Shrivastava, Faisal Sohail, Saten Kumar, Ronald Peeters, Matthew Read and seminar participants at the Asia Meeting of the Econometric Society, Auckland University of Technology, Curtin University, Delhi School of Economics, Indian Institute of Management Bangalore, Indian Statistical Institute, Monash University, National Bank of Belgium, Reserve Bank of Australia, Reserve Bank of India, Reserve Bank of New Zealand, Singapore Management University, University of Auckland, University of New South Wales, University of Otago, University of Sydney, University of Western Australia, and Victoria University of Wellington for helpful comments and suggestions.

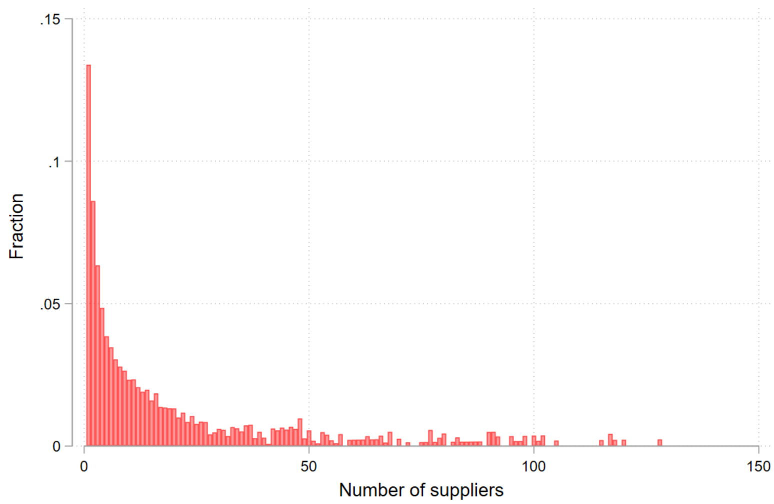

Figure A.2: Distribution of Firms' Number of Suppliers

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.

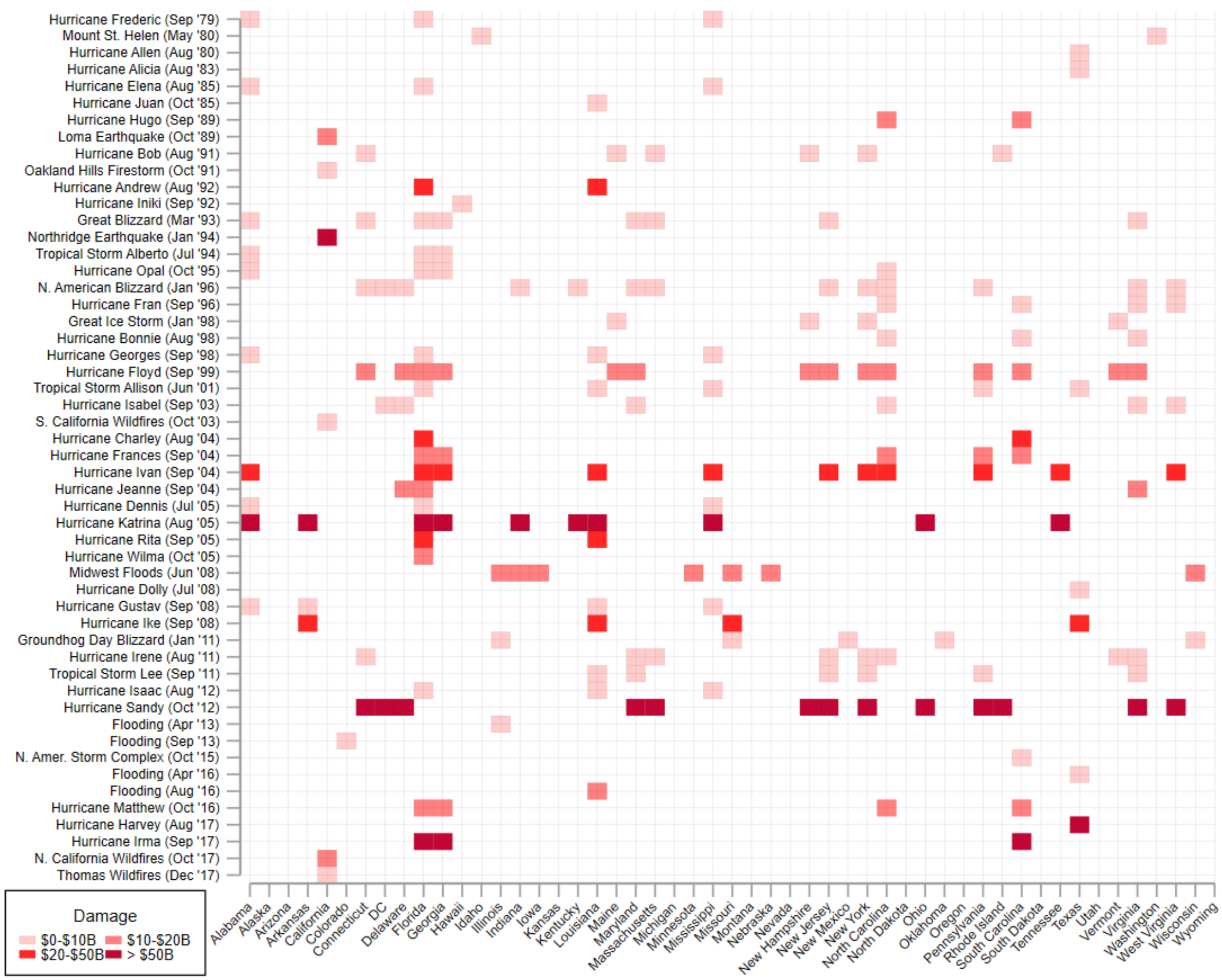

Figure A.3: Major Natural Disasters by US States (1978-2017)

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.

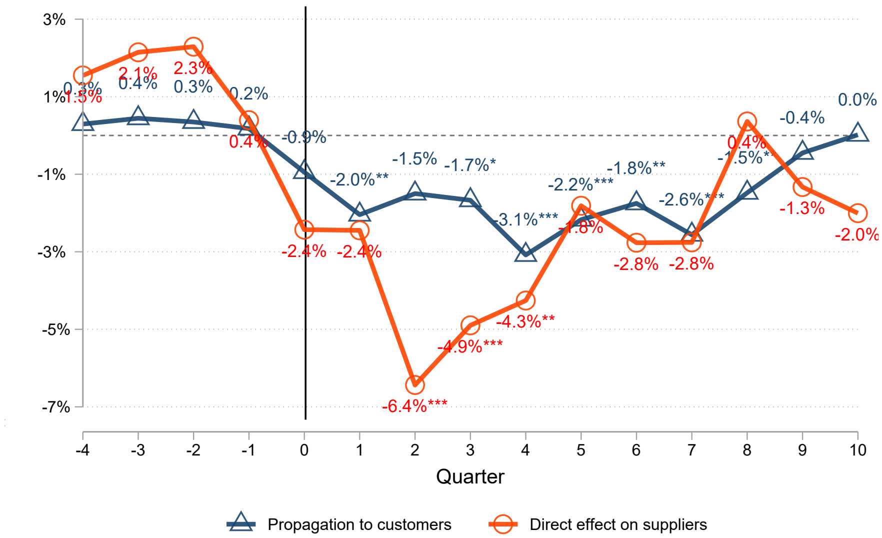

Figure A.4: The Direct and Indirect Effect of Shocks on Firms' Sales Growth

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

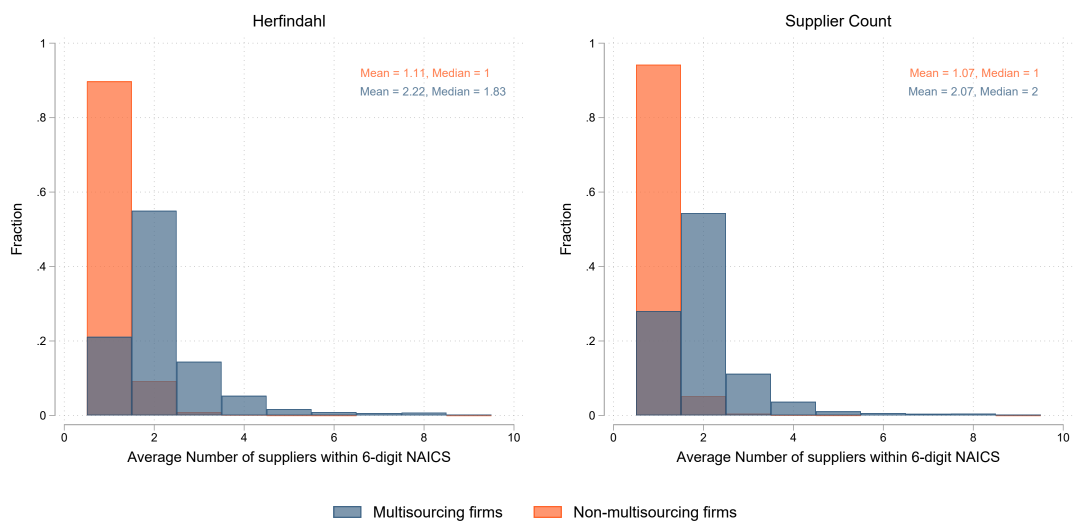

Figure A.5: Distribution of Firms' Number of Suppliers Within 6-digit NAICS Industries

Note: This figure shows the distribution of suppliers within 6-digit NAICS industries for multi- and non-multisourcing firms (as measured by Equations 4 and 6, respectively). For visibility, we show the distributions up to ten suppliers (on the horizontal axis), which covers more than 99 percent of each distribution.

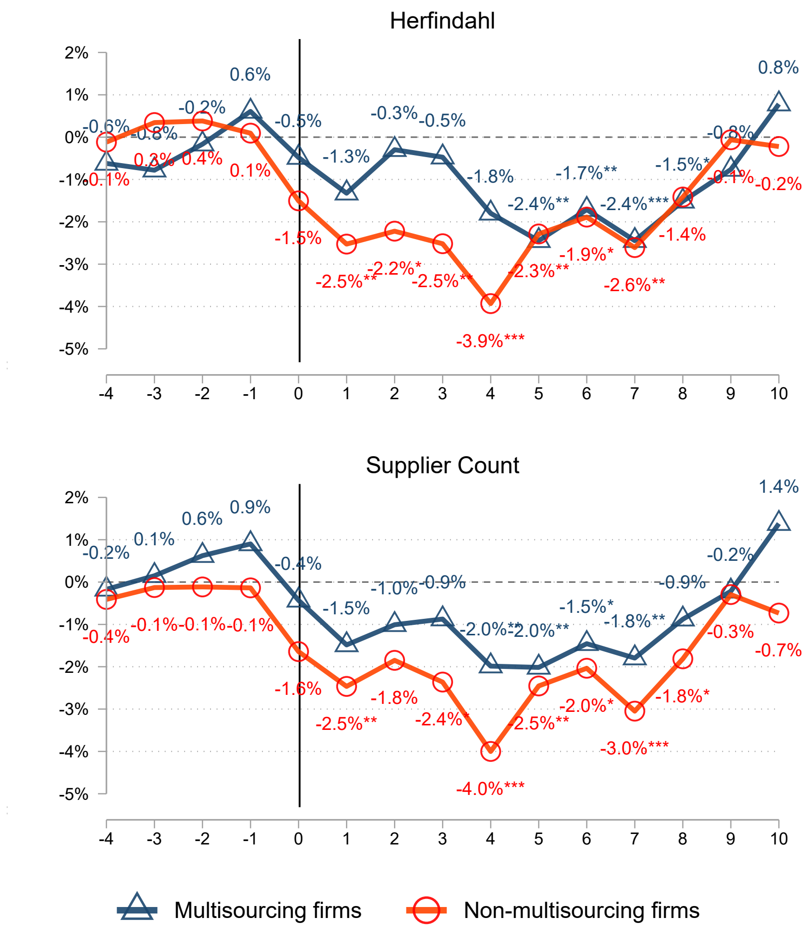

Figure A.6: Contemporaneous Multisourcing and Shock Propagation

Note: This figure presents estimates relating to regression specification (7), augmented by interacting multisourcing dummies with the indicator $\mathbb{I}[\textit{Shock hits iI's supp.}]_{t-k}$ at the time of the shocks. Specifically, we estimate

$$\Delta \log Q_{iI,t} = \alpha + \sum_{k=-4}^{10} \beta_k \cdot \mathbb{I}[\text{Shock hits } iI]_{t-k} + \sum_{k=-4}^{10} \gamma_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} + \delta \cdot \mathbb{I}[iI \text{ Multisources}]_{t-k}$$

$$+ \sum_{k=-4}^{10} \kappa_k \cdot \mathbb{I}[\text{Shock hits } iI\text{'s supp.}]_{t-k} \times \mathbb{I}[iI \text{ Multisources}]_{t-k} + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t}.$$

The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. In the top panel, multisourcing is measured using firms' supplier HHIs (as defined in Equation 4). In the bottom panel, multisourcing is measured using supplier counts (Equation 6). Blue lines plot estimates of the propagation of shocks to multisourcing firms ($\hat{\gamma} + \hat{\kappa}$), whereas orange lines plot propagation to non-multisourcing firms ($\hat{\gamma}$). All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, industry- and state-time fixed effects, and control variables for firms' number of suppliers, number of employees, level of inventory and age. The regressions also include 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.

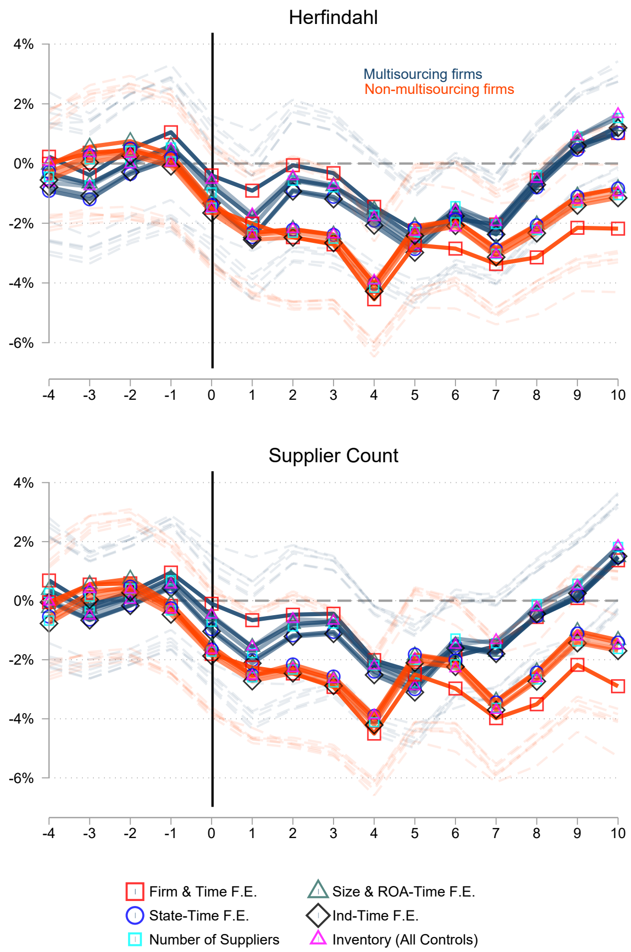

Figure A.7: The Effect of Multisourcing on Shock Propagation (Robustness)

Note: This figure shows results for different versions of specification (7), with the progressive inclusion of firm, time, size, return on assets (ROA) by quarter, state-time, and industry-time fixed effects and control variables for firms' number of suppliers and level of inventory. The final specification includes a tercile dummy of firms' inventory-to-sales ratio. Dashed lines represent 95% confidence intervals. Standard errors are clustered at the firm level.

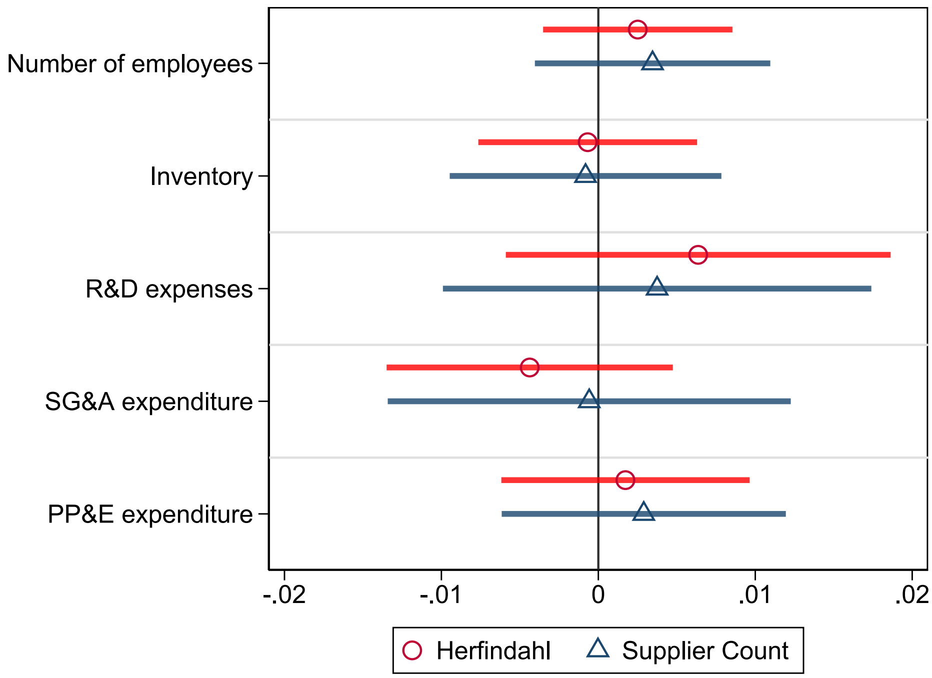

Figure A.8: Orthogonality of Multisourcing Measures with Other Firm Attributes

Note: This figure presents results from regressions of each multisourcing indicator on the firm attribute listed on the vertical axis and all other controls specification (7). *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.

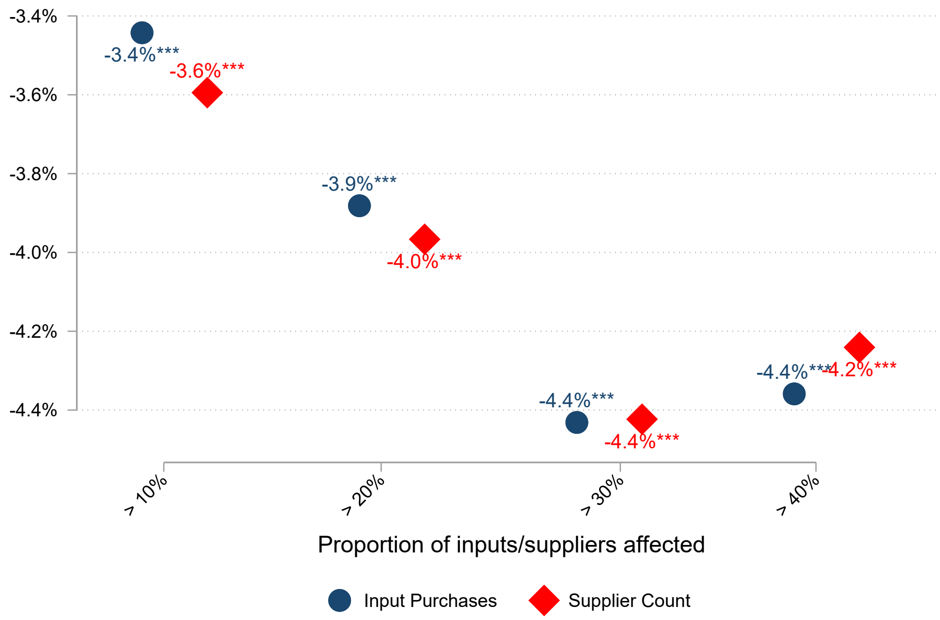

Figure A.9: Intensity of Supply Chain Disruptions and Customers' Sales Growth

Note: The figure presents estimates relating to the specification:

$$\Delta \log Q_{iI,t} = \alpha + \beta \cdot \mathbb{I}[\text{Shock hits } iI]_{t-4} + \gamma \cdot \mathbb{I}[\text{Shock Intensity} > x\%]_{iI,t-4} + \mathbf{X}'_{iI,t}\boldsymbol{\lambda} + \tau_t + \eta_{iI} + \varepsilon_{iI,t},$$

where $\mathbb{I}[\text{Shock Intensity} > x\%]_{iI,t-4}$ is an indicator that takes the value one if *Shock Intensity*$_{iI,t-4} > x\%$ and zero otherwise, for thresholds $x \in \{10, 20, 30, 40\}$. We run separate regressions for each threshold x and *Shock Intensity* measure (Equations 9 and 11). We focus on the fourth lag, as this is when we observe the greatest propagation of supply chain disruptions to customer firms. We limit the threshold to 40% of inputs/suppliers affected, as firms with more than 40% typically have only one affected supplier. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. Blue points correspond to the measure *Shock Intensity*$^{\text{Input}}$ which uses information on input purchases, as in Equation (9), while the red points relate to the measure *Shock Intensity*$^{\text{Count}}$, which uses information on supplier counts, as in Equation (11). 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, age, size and return on assets. Standard errors are clustered at the firm level. *10%; **5%; ***1% significance levels.

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]
Shock hits firm control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter & fiscal 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 control	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 year-on-year sales growth. The regressions include all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects and fiscal quarter fixed effects. Columns (2), (3), and (4) progressively add year-quarter fixed effects, dummy variables for the tercile of firm size and ROA interacted with year-quarter fixed effects and control variables for firms' number of suppliers, number of customers and age. Standard errors (reported in square brackets) are clustered at the firm level. *10%; **5%; ***1% significance levels.

Table A.2: Downstream Propagation with Randomly Identified Multisourcing Firms

Multisourcing measure	Herfindahl		Supplier Count	
	(1)	(2)	(3)	(4)
Shock hits one of multisourcing firm's suppliers $(t-4)$	0.010	0.015	-0.010	-0.009
	[0.028]	[0.028]	[0.019]	[0.019]
Shock hits at least one supplier $(t-4)$	-0.033***	-0.032***	-0.031***	-0.029***
	[0.008]	[0.008]	[0.008]	[0.008]
Shock hits firm control $(t-4)$	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter & fiscal quarter FE	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes
Number of suppliers control	Yes	Yes	Yes	Yes
Multisourcing firm control	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes
Observations	95,455	95,455	95,455	95,455
Adjusted R^2	0.202	0.220	0.202	0.220

Notes: This table presents estimates for regression (7) but where customers are randomly classified as multisourcing firms. 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), and (4) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter fixed effects. The regressions only include the fourth lag since this is when we observe the greatest propagation to customer firms. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

Table A.3: Multisourcing and Bargaining Power

Multisourcing measure	Herfindahl		Count	
	(1)	(2)	(3)	(4)
Disaster hits one of multisourcing firm's suppliers $(t-4)$	0.037***	0.029**	0.032**	0.024*
	[0.014]	[0.013]	[0.014]	[0.014]
Disaster hits one supplier $(t-4)$	-0.046***	-0.040***	-0.047***	-0.041***
	[0.010]	[0.010]	[0.011]	[0.011]
Bargaining power × Disaster hits one supplier $(t-4)$	0.003	0.001	0.002	0.001
	[0.014]	[0.013]	[0.014]	[0.013]
Bargaining power	0.007	0.010	0.009	0.011
	[0.008]	[0.008]	[0.008]	[0.008]
Firm FE	Yes	Yes	Yes	Yes
Year-quarter & fiscal quarter FE	Yes	Yes	Yes	Yes
Number of suppliers control	Yes	Yes	Yes	Yes
Multisourcing firm control	Yes	Yes	Yes	Yes
Shock hits firm control	Yes	Yes	Yes	Yes
Size & ROA × year-quarter FE	No	Yes	No	Yes
Observations	95,303	95,303	95,303	95,303
Adjusted R^2	0.202	0.219	0.202	0.219

Notes: This table presents estimates for specification (7), but with two additional regressors: a measure of firms' *bargaining power*, based on Ahern (2012), and an interaction of *bargaining power* and a dummy variable indicating if at least one of the firm's suppliers was hit by a disaster four quarters back. A customer firm's bargaining power over each supplier is first computed by calculating the ratio of the customer's purchases from the supplier to the supplier's total sales. We drop observations where this ratio is negative or greater than one. The *bargaining power* in quarter t is then the weighted average of this ratio across all suppliers, where the weights are the customer's purchases from each supplier as a share of the customer's total purchases in that quarter. Firms in the top tercile of this variable in quarter t are classified as high bargaining power firms and are assigned a value of one in the *bargaining power* variable. All other firms are assigned a value of zero. The dependent variable in the regressions is firms' sales growth relative to the same quarter in the previous year. The regressions also include a dummy that indicates whether a natural disaster hit the firm. 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), and (4) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter fixed effects. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

Table A.4: Correcting for Potential Bias in Staggered Difference-in-Differences

	Herfindahl		Supplier Count	
	Non-multisourcing	Multisourcing	Non-multisourcing	Multisourcing
Disaster hits at least one supplier $(t-4)$	-0.043***	-0.011**	-0.036***	-0.018***
	[0.014]	[0.004]	[0.013]	[0.005]
Firm FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	74,464	74,464	74,464	74,464
Adjusted R^2	0.240	0.240	0.240	0.240

Notes: This table reports estimates for regression specification (14). We run separate regressions for the Herfindahl and supplier count measures of multisourcing, defined in Equations (4) and (6), respectively. The coefficient estimates account for potential bias from (i) staggered treatment timing and (ii) heterogeneous treatment effects across disaster events, following Wooldridge (2021). Treated firms are compared with not-yet-treated and never-treated firms, and the effects of supplier shocks are estimated separately for each event quarter, then aggregated using the shares of treated multi- and non-multisourcing firms in each quarter. All regressions include firm fixed effects, year-quarter fixed effects, and interactions of time effects with return on assets, total assets, fiscal quarter dummies, age, number of employees, hits-firm dummies, and number of suppliers. The regressions also include centered dummies for return on assets, fiscal quarters, total assets, age, number of employees, hits-firm status, and number of suppliers, all interacted with event dummies. Standard errors, reported in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

Table A.5: Independence of Multisourcing and Disasters (Intensive Margin)

Multisourcing measure	Herfindahl		Supplier Count	
	(1)	(2)	(3)	(4)
Number of supplier disruptions in the past five years	0.000	0.001	0.001	0.002
	[0.001]	[0.001]	[0.002]	[0.002]
Number of disasters in the past five years	0.001	0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.003]	[0.003]
Firm FE	Yes	Yes	Yes	Yes
Year-quarter & fiscal quarter FE	Yes	Yes	Yes	Yes
Number of suppliers control	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes
Observations	95,455	95,455	95,455	95,455
Adjusted R^2	0.495	0.497	0.521	0.527

Notes: The table presents estimates relating to regression specification (15). The regression includes all firm-quarters from 1978 to 2017 in Compustat's *Customer Segments* dataset. All regressions include firm fixed effects, year-quarter fixed effects, fiscal quarter fixed effects, and control variables for firms' number of suppliers, number of employees and age. Columns (2) and (4) also include dummy variables for the tercile of firm size, and ROA interacted with year-quarter dummies. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

Table A.6: Creation of New Links and the Destruction of Existing Links

	New links forming		Existing links ending	
	(1)	(2)	(3)	(4)
County's number of disasters in the past five years	0.016** [0.006]	-0.001 [0.004]	0.016** [0.006]	-0.002 [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: Columns 1 and 2 report estimates for Equation (16), whereas columns 3 and 4 report estimates for Equation (17). The unit of observation is a county-year. Natural disaster data are from *EM-DAT* and *OpenFEMA Disaster Declarations* datasets. We use Computstat's *Customer Segments* dataset for information on interfirm linkages. *10%; **5%; ***1% significance levels.

Table A.7: The Effect of Natural Disasters on Suppliers of Multisourcing Firms

Multisourcing measure	Herfindahl		Supplier Count	
	(1)	(2)	(3)	(4)
Natural disaster hits firm with a multisourcing customer $(t, t-8)$	-0.001 [0.018]	-0.003 [0.017]	-0.002 [0.018]	-0.002 [0.017]
Natural disaster hits firm $(t, t-8)$	-0.032** [0.014]	-0.030** [0.014]	-0.032** [0.015]	-0.031** [0.014]
Multisourcing customer control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-quarter & fiscal quarter FE	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes
Observations	175,685	175,685	175,685	175,685
Adjusted R^2	0.130	0.137	0.130	0.137

Notes: This table shows results relating to Equation (1) but with two additional controls: *Multisourcing customer* and *Disaster hits firm with a multisourcing customer (t,t - 8)*. *Multisourcing customer* is an indicator that takes a value one if a supplier firm has at least one customer identified as a multisourcing firm at time *t*. *Disaster hits firm with a multisourcing customer (t,t - 8)* is an indicator of disasters hitting the supplier firm anytime between (*t*) and (*t* - 8), interacted with the *multisourcing customer* dummy. Each column reports a separate regression. All regressions include firm, fiscal-quarter, and year-quarter fixed effects, as well as the multisourcing customer control and control variables for firms' number of employees and age. Columns (2) and (4) also include size and return on assets controls interacted with year-quarter dummies. Standard errors, shown in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

Table A.8: Orthogonality of Multisourcing and Input Specificity (Patent)

Multisourcing measure	Herfindahl		Supplier Count	
	(1)	(2)	(3)	(4)
Disaster hits one of multisourcing firm's suppliers $(t-4)$	0.041***	0.033**	0.032**	0.026*
	[0.013]	[0.013]	[0.014]	[0.014]
Disaster hits specific supplier $(t-4)$	-0.031**	-0.032***	-0.030**	-0.031**
	[0.013]	[0.012]	[0.013]	[0.013]
Disaster hits one supplier $(t-4)$	-0.039***	-0.036***	-0.039***	-0.036***
	[0.010]	[0.010]	[0.011]	[0.011]
Firm FE	Yes	Yes	Yes	Yes
Year-quarter & fiscal quarter FE	Yes	Yes	Yes	Yes
Shock hits firm control	Yes	Yes	Yes	Yes
Multisourcing firm control	Yes	Yes	Yes	Yes
Specific supplier control	Yes	Yes	Yes	Yes
Age & number of employees controls	Yes	Yes	Yes	Yes
Number of suppliers control	Yes	Yes	Yes	Yes
Size & ROA $\times$ year-quarter FE	No	Yes	No	Yes
Observations	86,093	86,093	86,093	86,093
Adjusted R^2	0.202	0.220	0.202	0.220

Notes: This table presents estimates for specification (7), but with the inclusion of a dummy that indicates whether the firm has a specific supplier (as measured by the number of patents measure of Barrot and Sauvagnat, 2016) and an interaction between this *specific supplier* dummy and the indicator $\mathbb{I}[\textit{Shock hits iI's supp.}]_{t-4}$. 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) and (4) also include dummy variables for the tercile of firm size and ROA interacted with year-quarter fixed effects. Standard errors, represented in square brackets, are clustered at the firm level. *10%; **5%; ***1% significance levels.

B Data appendix

B.1 Firm financial data

Compustat's *North America Fundamentals Quarterly* database 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.[2] We deflate sales and cost of goods sold (COGS) using the GDP price index from the Bureau of Economic Analysis so that growth in these variables reflects firms' performance, not price dynamics.[3]

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 financials with natural disasters, which are also reported at the calendar quarter-county level.[4] 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.

B.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).[5] Since a firm's location may change over time, we achieve greater accuracy 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'

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

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

[4]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.

[5]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.

sales.

We match the adjusted ZIP codes to the *US ZIP Codes* database, which contains the latitude and longitude for all 41,696 private and USPS ZIPs.[6] 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.

B.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.[7] A limitation of this data 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 propagation of supply shocks to customers, with some control group observations actually being treated. Crucially, the 10% threshold does not bias firms' in-degree distribution (Atalay et al., 2011) or our empirical multisourcing measures.

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

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

[7] 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.

(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.

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.

B.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 damage.[8] 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

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

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.

C Proofs

Derivation of Equation (23). We begin by presenting three interim results. First, we characterize changes in firm-level prices in response to capital-augmenting shocks. Second, we express the steady-state Leontief inverse in terms of multisourcing HHIs. Third, we characterize how the Leontief inverse parameters respond to shocks.

1. Price changes. From firms' optimization, we derive optimal values for x_{iI}^{jJ} and k_{iI}:

$$x_{iI}^{jJ} = \mu_I^{-1} p_{iI}(1-\alpha) Q_{iI} \omega_I^J P_J{}^{\rho-1} p_{jJ}^{-\rho}, \tag{C.1}$$

$$k_{iI} = \alpha \mu_I^{-1} p_{iI} Q_{iI} r^{-1}. \tag{C.2}$$

Substituting Equation (C.1) into Equation (19), we get

$$X_{iI}^{J} = \mu_I^{-1} p_{iI}(1-\alpha) \omega_I^J Q_{iI} P_J^{-1}. \tag{C.3}$$

Plugging Equation (C.3) into the industry-level intermediates aggregator M_{iI}, yields

$$M_{iI} = \mu_I^{-1} p_{iI}(1-\alpha) Q_{iI} \mathcal{P}_I{}^{-1}. \tag{C.4}$$

From Equations (C.1) and (C.3), we get

$$\Phi_{iI}^{jJ} = \left(\frac{p_{jJ}}{P_J}\right)^{1-\rho} = \left(\frac{p_{jJ}^{1-\rho}}{\sum_{j\in N_J} p_{jJ}^{1-\rho}}\right). \tag{C.5}$$

Substituting Equations (C.2) and (C.4) into firm $i \in N_I$'s production function, we get

$$p_{iI} = \mu_I z_{iI}{}^{-\alpha} \alpha^{-\alpha} r^{\alpha} (1-\alpha)^{\alpha-1} \mathcal{P}_I^{1-\alpha}. \tag{C.6}$$

Total differentiation of Equation (C.6), yields

$$d\log p_{iI} = -\alpha d\log z_{iI} + \sum_{J\in N} \sum_{j\in N_J} \Omega_{iI}^{jJ} d\log p_{jJ},$$

which uses the result that $\Omega_{iI}^{jJ} = (1-\alpha)\omega_I^J P_J^{\rho-1} p_{jJ}^{1-\rho}$. Rearranging to solve for $d\log p_{iI}$, we get

$$d\log p_{iI} = -\alpha \sum_{J\in N} \sum_{j\in N_J} \psi_{iI}^{jJ} d\log z_{jJ}. \tag{C.7}$$

2. Steady-state Leontief inverse. Next, we characterize the steady-state Leontief inverse. Note that the iI, jJ^{th} element of $\mathbf{\Psi}$ is given by

$$\psi_{iI}^{jJ} = \delta_{iI}^{jJ} + \Omega_{iI}^{jJ} + \sum_{M\in N} \sum_{m\in N_M} \Omega_{iI}^{mM} \Omega_{mM}^{jJ} + \ldots \tag{C.8}$$

where δ_{iI}^{jJ} is the Kronecker delta. From Equations (C.1) and (C.5), it follows that

$$\Omega_{iI}^{jJ} = (1-\alpha)\omega_I^J \Phi_{iI}^{jJ}. \tag{C.9}$$

In steady-state, (C.8) can be written as

$$\psi_{iI}^{jJ} = \delta_{iI}^{jJ} + \mathcal{M}_{iI}^{J} \beta_I^J. \tag{C.10}$$

where

$$\beta_I^J \equiv (1-\alpha)\omega_I^J + (1-\alpha)^2 \sum_{M\in N} \omega_I^M \omega_M^J + \ldots \tag{C.11}$$

3. Changes in the Leontief inverse. Finally, we characterize $\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}$. Begin by noting that $d\mathbf{\Psi} = \mathbf{\Psi} d\mathbf{\Omega}\mathbf{\Psi}$, with iI, kK^{th} element given by

$$d\psi_{iI}^{kK} = \sum_{M\in N} \sum_{m\in N_M} \sum_{S\in N} \sum_{s\in N_S} \psi_{iI}^{sS} \psi_{mM}^{kK} \Omega_{sS}^{mM} d\log \Omega_{sS}^{mM}.$$

From Equation (C.9), it follows that $d\log \Omega_{sS}^{mM} = d\log \Phi_{sS}^{mM}$. The above equation can then be written as

$$d\psi_{iI}^{kK} = \sum_{M\in N} \sum_{m\in N_M} \sum_{S\in N} \sum_{s\in N_S} \psi_{iI}^{sS} \psi_{mM}^{kK} \Omega_{sS}^{mM} d\log \Phi_{sS}^{mM}. \tag{C.12}$$

Using Equation (C.5) and Equation (C.7), it follows that

$$\frac{d\log \Phi_{sS}^{mM}}{d\log z_{kK}} = (1-\rho)\left(\frac{d\log p_{mM}}{d\log z_{kK}} - \sum_{r\in N_M} \Phi_{sS}^{rM} \frac{d\log p_{rM}}{d\log z_{kK}}\right) = \alpha(1-\rho)\left(\sum_{r\in N_M} \Phi_{sS}^{rM} \psi_{rM}^{kK} - \psi_{mM}^{kK}\right),$$

which, in steady-state simplifies to

$$\frac{d\log\Phi_{sS}^{mM}}{d\log z_{kK}}=\alpha(1-\rho)\left(\sum_{r\in N_M}\frac{1}{N_M}\delta_{rM}^{kK}-\delta_{mM}^{kK}\right).$$

Therefore, from Equation (C.12), we get

$$\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}=\alpha(1-\rho)\sum_{M\in N}\sum_{m\in N_M}\sum_{S\in N}\sum_{s\in N_S}\psi_{iI}^{sS}\psi_{mM}^{kK}\Omega_{sS}^{mM}\left(\frac{1}{N_M}\sum_{r\in N_M}\delta_{rM}^{kK}-\delta_{mM}^{kK}\right),$$

$$\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}=\alpha(1-\rho)\sum_{m\in N_K}\sum_{S\in N}\sum_{s\in N_S}\psi_{iI}^{sS}\psi_{mK}^{kK}\Omega_{sS}^{mK}\left(\frac{1}{N_K}-\delta_{mK}^{kK}\right).$$

The above equation simplifies to

$$\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}=\alpha(1-\rho)\left(\frac{1}{N_K}\sum_{m\in N_K}\left(\sum_{S\in N}\sum_{s\in N_S}\psi_{iI}^{sS}\Omega_{sS}^{mK}\right)\psi_{mK}^{kK}-\psi_{kK}^{kK}\left(\sum_{S\in N}\sum_{s\in N_S}\psi_{iI}^{sS}\Omega_{sS}^{kK}\right)\right).$$

Noting that $\sum_{S\in N}\sum_{s\in N_S}\psi_{iI}^{sS}\Omega_{sS}^{mK}=\psi_{iI}^{mK}-\delta_{iI}^{mK}$ and $\sum_{S\in N}\sum_{s\in N_S}\psi_{iI}^{sS}\Omega_{sS}^{kK}=\psi_{iI}^{kK}-\delta_{iI}^{kK}$, we get

$$\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}=\alpha(1-\rho)\left(\frac{1}{N_K}\sum_{m\in N_K}\left(\psi_{iI}^{mK}-\delta_{iI}^{mK}\right)\psi_{mK}^{kK}-\psi_{kK}^{kK}\left(\psi_{iI}^{kK}-\delta_{iI}^{kK}\right)\right).$$

Finally, by (C.10), the above can be written as

$$\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}=\alpha(\rho-1)\beta_I^K\mathcal{M}_{iI}^K\left(1-\mathcal{M}_{iI}^K\right)+\alpha(\rho-1)\mathcal{M}_{iI}^K\left(\sum_{m\in N_K}\delta_{iI}^{mK}-\delta_{iI}^{kK}\right).\tag{C.13}$$

Changes in output. We now turn to the main part of the proof. Our task is to characterize

$$\Delta\log Q_{iI}\approx\frac{d\log Q_{iI}}{d\log z_{kK}}\left(\Delta\log z_{kK}\right)+\frac{1}{2}\frac{d^2\log Q_{iI}}{d\log z_{kK}^2}\left(\Delta\log z_{kK}\right)^2.\tag{C.14}$$

We begin with $\frac{d\log Q_{iI}}{d\log z_{kK}}$. With some manipulation of the goods market-clearing condition for firm $i\in N_I$, we get

$$p_{iI}Q_{iI}\frac{1}{\mu_I}=p_{iI}C_{iI}+\sum_{J\in N}\sum_{j\in N_J}\Omega_{jJ}^{iI}\frac{1}{\mu_J}p_{jJ}Q_{jJ}.$$

Total differentiation of the above equation, gives

$$\frac{1}{\mu_I}d\left(p_{iI}Q_{iI}\right)-\sum_{J\in N}\sum_{j\in N_J}\frac{1}{\mu_J}\Omega_{jJ}^{iI}d\left(p_{jJ}Q_{jJ}\right)=d\left(p_{iI}C_{iI}\right)+\sum_{J\in N}\sum_{j\in N_J}\frac{1}{\mu_I}p_{jJ}Q_{jJ}d\Omega_{jJ}^{iI}.$$

In matrix form

$$d(\mathbf{pQ})'\text{diag}(\boldsymbol{\mu})^{-1} - d(\mathbf{pQ})'\text{diag}(\boldsymbol{\mu})^{-1}\boldsymbol{\Omega} = d(\mathbf{pC})' + (\mathbf{pQ})'\text{diag}(\boldsymbol{\mu})^{-1}d\boldsymbol{\Omega},$$

where $\mathbf{pQ}$ is a $\sum_{J\in N} N_J \times 1$ vector of firm-level total sales, $\mathbf{pC}$ is a $\sum_{J\in N} N_J \times 1$ vector of firm-level final consumption expenditure and $\boldsymbol{\mu}$ is an $\sum_{J\in N} N_J \times 1$ vector of markups. Solving for $d(\mathbf{pQ})$:

$$d(\mathbf{pQ})'\text{diag}(\boldsymbol{\mu})^{-1} = d(\mathbf{pC})'\boldsymbol{\Psi} + (\mathbf{pQ})'\text{diag}(\boldsymbol{\mu})^{-1}d\boldsymbol{\Omega}\boldsymbol{\Psi}.$$

The iI^{th} element of $d(\mathbf{pQ})$ is thus given by

$$\frac{1}{\mu_I}d\left(p_{iI}Q_{iI}\right) = \sum_{J\in N}\sum_{j\in N_J}\psi_{jJ}^{iI}d\left(p_{jJ}C_{jJ}\right) + \sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M} p_{mM}Q_{mM}\frac{1}{\mu_M}\psi_{jJ}^{iI}d\Omega_{mM}^{jJ}.$$

Noting that $\Omega_{mM}^{jJ} = (1-\alpha)\omega_M^J\Phi_{mM}^{jJ}$ and $d\log\Omega_{mM}^{jJ} = d\log\Phi_{mM}^{jJ}$, we get

$$\frac{1}{\mu_I}d\left(p_{iI}Q_{iI}\right) = \sum_{J\in N}\sum_{j\in N_J}\psi_{jJ}^{iI}d\left(p_{jJ}C_{jJ}\right) + \sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M}(1-\alpha)\omega_M^J\Phi_{mM}^{jJ}p_{mM}Q_{mM}\frac{1}{\mu_M}\psi_{jJ}^{iI}d\log\Phi_{mM}^{jJ}.$$

Further, noting that $d\left(p_{jJ}C_{jJ}\right) = 0$ (since $d\left(p_{jJ}C_{jJ}\right) = p_{jJ}C_{jJ}d\log\theta - p_{jJ}C_{jJ}d\log\text{GDP} = 0$), $\frac{p_{mM}Q_{mM}}{p_{iI}Q_{iI}}\frac{\mu_I}{\mu_M} = \frac{\lambda_{mM}}{\lambda_{iI}}$, and $d\log\Phi_{mM}^{jJ} = (1-\rho)\left(d\log p_{jJ} - \sum_{s\in N_J}\Phi_{mM}^{sJ}d\log p_{sJ}\right)$ we get

$$d\log Q_{iI} = (1-\rho)(1-\alpha)\sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M}\omega_M^J\Phi_{mM}^{jJ}\frac{\lambda_{mM}}{\lambda_{iI}}\psi_{jJ}^{iI}\left(d\log p_{jJ} - \sum_{s\in N_J}\Phi_{mM}^{sJ}d\log p_{sJ}\right) - d\log p_{iI}.$$

Therefore,

$$\frac{d\log Q_{iI}}{d\log z_{kK}} = (1-\rho)(1-\alpha)\sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M}\omega_M^J\Phi_{mM}^{jJ}\frac{\lambda_{mM}}{\lambda_{iI}}\psi_{jJ}^{iI}\left(\frac{d\log p_{jJ}}{d\log z_{kK}} - \sum_{s\in N_J}\Phi_{mM}^{sJ}\frac{d\log p_{sJ}}{d\log z_{kK}}\right) - \frac{d\log p_{iI}}{d\log z_{kK}}. \tag{C.15}$$

Using Equation (C.7), we can express the above equation as

$$\frac{d\log Q_{iI}}{d\log z_{kK}} = \chi_{iI}^{kK} + \alpha\psi_{iI}^{kK}, \tag{C.16}$$

where

$$\chi_{iI}^{kK} \equiv (1-\rho)\alpha(1-\alpha)\sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M}\omega_M^J \Phi_{mM}^{jJ}\frac{\lambda_{mM}}{\lambda_{iI}}\psi_{jJ}^{iI}\left(\sum_{s\in N_J}\Phi_{mM}^{sJ}\psi_{sJ}^{kK}-\psi_{jJ}^{kK}\right).$$

The second-order impact of the shock can then be expressed as

$$\frac{d^2\log Q_{iI}}{d\log z_{kK}^2} = \chi_{iI}^{kK}\frac{d\log\chi_{iI}^{kK}}{d\log z_{kK}} + \alpha\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}.$$

Equation (C.14) thus becomes

$$\Delta\log Q_{iI} \approx \left(\chi_{iI}^{kK}+\alpha\psi_{iI}^{kK}\right)(\Delta\log z_{kK}) + \frac{1}{2}\left(\chi_{iI}^{kK}\frac{d\log\chi_{iI}^{kK}}{d\log z_{kK}}+\alpha\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}\right)(\Delta\log z_{kK})^2. \quad \text{(C.17)}$$

We now characterize the steady-state value of χ_{iI}^{kK}.

$$\chi_{iI}^{kK} = \alpha(1-\alpha)(1-\rho)\sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M}\omega_M^J\Phi_{mM}^{jJ}\frac{\lambda_{mM}}{\lambda_{iI}}\psi_{jJ}^{iI}\left(\frac{1}{N_J}\sum_{s\in N_J}\delta_{sJ}^{kK}-\delta_{jJ}^{kK}\right),$$

$$\chi_{iI}^{kK} = \alpha(1-\rho)(1-\alpha)\frac{1}{N_K}\lambda_{iI}^{-1}\left(\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\lambda_{mM}\right)\left(\frac{1}{N_K}\sum_{j\in N_K}\sum_{s\in N_K}\psi_{jK}^{iI}\delta_{sK}^{kK}-\sum_{j\in N_K}\psi_{jK}^{iI}\delta_{jK}^{kK}\right),$$

$$\chi_{iI}^{kK} = \alpha(1-\rho)(1-\alpha)\frac{1}{N_K}\lambda_{iI}^{-1}\left(\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\lambda_{mM}\right)\left(\frac{1}{N_K}\sum_{j\in N_K}\psi_{jK}^{iI}-\psi_{kK}^{iI}\right),$$

$$\chi_{iI}^{kK} = \alpha(1-\rho)(1-\alpha)\frac{1}{N_K}\lambda_{iI}^{-1}\left(\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\lambda_{mM}\right)\left(\frac{1}{N_K}\sum_{j\in N_K}\delta_{jK}^{iI}-\delta_{kK}^{iI}\right)=0,$$

since $\left(\frac{1}{N_K}\sum_{j\in N_K}\delta_{jK}^{iI}-\delta_{kK}^{iI}\right)=0$. Equation (C.17) then becomes

$$\Delta\log Q_{iI} \approx \left(\alpha\psi_{iI}^{kK}\right)(\Delta\log z_{kK}) + \frac{1}{2}\alpha\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}(\Delta\log z_{kK})^2.$$

Finally, using Equations (C.10) and (C.13), the above equation can be written as

$$\Delta\log Q_{iI} \approx \alpha\beta_I^K\mathcal{M}_{iI}^K\left(\Delta\log z_{kK}+\frac{\alpha}{2}(\rho-1)\left(1-\mathcal{M}_{iI}^K\right)(\Delta\log z_{kK})^2\right),$$

for $I\neq K$.

$\blacksquare$

Derivation of Equations (24) and (25). We first characterize the change in firm $i \in N_I$'s consumption of intermediate inputs from an unaffected firm m in industry K in response to a shock to firm $k \in N_K$. Total differentiation of Equation (C.1) implies

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = \frac{d\log p_{iI}}{d\log z_{kK}} + \frac{d\log Q_{iI}}{d\log z_{kK}} + (\rho-1)\frac{d\log P_K}{d\log z_{kK}} - \rho\frac{d\log p_{mK}}{d\log z_{kK}}.$$

Since $\frac{d\log Q_{iI}}{d\log z_{kK}} = -\frac{d\log p_{iI}}{d\log z_{kK}}$, for $I \neq K$, we get

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = (\rho-1)\sum_{s\in N_K}\Phi_{iI}^{sK}\frac{d\log p_{sK}}{d\log z_{kK}} - \rho\frac{d\log p_{mK}}{d\log z_{kK}}.$$

Using Equation (C.7), the above equation becomes:

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = \alpha\rho\psi_{mK}^{kK} - \alpha(\rho-1)\sum_{s\in N_K}\Phi_{iI}^{sK}\psi_{sK}^{kK}.$$

In steady-state, the above equation can be written as:

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = \alpha\rho\left(\delta_{mK}^{kK} + \frac{1}{N_K}\beta_K^K\right) - \alpha(\rho-1)\sum_{s\in N_K}\frac{1}{N_K}\left(\delta_{sK}^{kK} + \frac{1}{N_K}\beta_K^K\right).$$

Simplifying, we get

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = \alpha\rho\left(\delta_{mK}^{kK} + \frac{1}{N_K}\beta_K^K\right) - \alpha(\rho-1)\frac{1}{N_K} - \alpha(\rho-1)\frac{1}{N_K}\beta_K^K,$$

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = \alpha\rho\delta_{mK}^{kK} + \alpha(1-\rho)\frac{1}{N_K} + \alpha\frac{1}{N_K}\beta_K^K.$$

Since $\beta_K^K\frac{1}{N_K} = \psi_{mK}^{kK} = \psi_{kK}^{kK} - 1$, and using the steady-state $\mathcal{M}_{iI}^K$, we can write

$$\frac{d\log x_{iI}^{mK}}{d\log z_{kK}} = (1-\rho)\alpha\mathcal{M}_{iI}^K + \alpha\psi_{mK}^{kK},$$

which is Equation (24) and

$$\frac{d\log x_{iI}^{kK}}{d\log z_{kK}} = \alpha(\rho-1)\left(1-\mathcal{M}_{iI}^K\right) + \alpha\psi_{kK}^{kK}.$$

which is Equation (25).

$\blacksquare$

Derivation of Equation (26). Our objective is to characterize:

$$\Delta \log Y \approx \frac{d\log Y}{d\log z_{kK}}\left(\Delta \log z_{kK}\right) + \frac{1}{2}\frac{d^2 \log Y}{d\log z_{kK}^2}\left(\Delta \log z_{kK}\right)^2. \tag{C.18}$$

We first characterize $\frac{d\log Y}{d\log z_{kK}}$. Start by noting that

$$d\log Y = -\sum_{I\in N}\sum_{i\in N_I}\Upsilon_{iI} d\log p_{iI},$$

since $d\log \mathrm{GDP} = 0$. Noting that $\Upsilon_{iI} = \theta$ and substituting Equation (C.7) into the above equation, yields

$$d\log Y = \alpha\theta \sum_{I\in N}\sum_{i\in N_I}\sum_{J\in N}\sum_{j\in N_J}\psi_{iI}^{jJ} d\log z_{jJ},$$

and

$$\frac{d\log Y}{d\log z_{kK}} = \alpha\theta\sum_{I\in N}\sum_{i\in N_I}\psi_{iI}^{kK}. \tag{C.19}$$

The second-order macroeconomic effect of the shock is then given by

$$\frac{d^2\log Y}{d\log z_{kK}^2} = \alpha\theta\sum_{I\in N}\sum_{i\in N_I}\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}. \tag{C.20}$$

Equation (C.18) can therefore be written as

$$\Delta\log Y \approx \alpha\theta\sum_{I\in N}\sum_{i\in N_I}\psi_{iI}^{kK}\left(\Delta\log z_{kK}\right) + \frac{1}{2}\alpha\theta\sum_{I\in N}\sum_{i\in N_I}\frac{d\psi_{iI}^{kK}}{d\log z_{kK}}\left(\Delta\log z_{kK}\right)^2. \tag{C.21}$$

Substituting Equations (C.10) and (C.13) into (C.21), yields

$$\begin{aligned}\Delta\log Y &\approx \alpha\theta\sum_{I\in N}\sum_{i\in N_I}\left(\delta_{iI}^{kK} + \beta_I^K\mathcal{M}_{iI}^K\right)\left(\Delta\log z_{kK}\right)\\ &+\frac{1}{2}\alpha\theta\sum_{I\in N}\sum_{i\in N_I}\left(\alpha(\rho-1)\beta_I^K\mathcal{M}_{iI}^K\left(1-\mathcal{M}_{iI}^K\right) + \alpha(\rho-1)\mathcal{M}_{iI}^K\left(\sum_{m\in N_K}\delta_{iI}^{mK} - \delta_{iI}^{kK}\right)\right)\left(\Delta\log z_{kK}\right)^2,\end{aligned}$$

which simplifies to

$$\begin{aligned}\Delta\log Y \approx \alpha\theta\left(1+\beta_K^K\mathcal{M}_{kK}^K\right)&\left(\Delta\log z_{kK} + \frac{\alpha}{2}(\rho-1)(1-\mathcal{M}_{kK}^K)\left(\Delta\log z_{kK}\right)^2\right)\\ &+\alpha\theta\sum_{I\in N}\sum_{\substack{i\in N_I\\ i\neq k\in N_K}}\beta_I^K\mathcal{M}_{iI}^K\times\left(\Delta\log z_{kK} + \frac{\alpha}{2}(\rho-1)(1-\mathcal{M}_{iI}^K)\left(\Delta\log z_{kK}\right)^2\right).\end{aligned}$$

■

Derivation of Equation (27)**.** Begin by recalling Equation (C.3): $X^K_{mM} = \mu_M^{-1} p_{mM}(1-\alpha)\omega^K_M Q_{mM} P_K^{-1}$. Multiplying by P_K and summing across all firms in industry M, we get

$$\sum_{m\in N_M} P_K X^K_{mM} = \sum_{m\in N_M} \mu_M^{-1} p_{mM} Q_{mM}(1-\alpha)\omega^K_M.$$

Noting that $TC_{mM} = \mu_M^{-1} p_{mM} Q_{mM}$ is mM's total costs, we define

$$\Omega^K_M \equiv \frac{\sum_{m\in N_M} P_K X^K_{mM}}{\sum_{m\in N_M} TC_{mM}} = (1-\alpha)\omega^K_M,$$

where Ω^K_M is the total expenditure by industry M on industry K as a share of M's total costs. Defining by

$$\lambda_M \equiv \sum_{m\in N_M} \lambda_{mM},$$

we can write

$$\sum_{M\in N} \Omega^K_M \lambda_M = \sum_{M\in N}\sum_{m\in N_M} \frac{P_K X^K_{mM}}{\text{GDP}}.$$

Finally, we divide by N_K and λ_{iK} to obtain the ratio of the average intermediate expenditure on industry K (as a share of GDP) to iK's Domar weight, which we denote by ς_{iK}:

$$\varsigma_{iK} = \frac{1}{N_K}\sum_{M\in N} \Omega^K_M \frac{\lambda_M}{\lambda_{iK}}.$$

We now turn to the main part of the proof. Note that, to a first-order approximation,

$$\Delta \log TC_{iI} \approx \sum_{K\in N}\sum_{k\in N_K} \frac{d\log TC_{iI}}{d\log z_{kK}}(\Delta \log z_{kK}).$$

Since $\frac{d\log \text{GDP}}{d\log z_{kK}} = 0$, the above can be written as

$$\Delta \log TC_{iI} \approx \sum_{K\in N}\sum_{k\in N_K} \frac{d\log \lambda_{iI}}{d\log z_{kK}}(\Delta \log z_{kK}).$$

Since $\frac{d\log \lambda_{iI}}{d\log z_{kK}} = 0$ for all $K \neq I$. The above equation can then be written as

$$\Delta \log TC_{iK} \approx \sum_{k\in N_K} \frac{d\log \lambda_{iK}}{d\log z_{kK}}(\Delta \log z_{kK}). \tag{C.22}$$

Our task is to characterize $\frac{d\log\lambda_{iK}}{d\log z_{kK}}$. From Equation (C.15), it follows that:

$$\frac{d\log\lambda_{iK}}{d\log z_{kK}} = \alpha(1-\alpha)(1-\rho)\sum_{J\in N}\sum_{j\in N_J}\sum_{M\in N}\sum_{m\in N_M}\omega_M^J\Phi_{mM}^{jJ}\frac{\lambda_{mM}}{\lambda_{iK}}\psi_{jJ}^{iK}\left(\sum_{s\in N_J}\Phi_{mM}^{sJ}\psi_{sJ}^{kK}-\psi_{jJ}^{kK}\right).$$

In steady-state, the above equation simplifies to:

$$\frac{d\log\lambda_{iK}}{d\log z_{kK}} = \alpha(1-\alpha)(1-\rho)\sum_{j\in N_K}\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\Phi_{mM}^{jK}\frac{\lambda_{mM}}{\lambda_{iK}}\psi_{jK}^{iK}\left(\sum_{s\in N_K}\frac{1}{N_K}\delta_{sK}^{kK}-\delta_{jK}^{kK}\right),$$

$$\frac{d\log\lambda_{iK}}{d\log z_{kK}} = \alpha(1-\alpha)(1-\rho)\sum_{j\in N_K}\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\Phi_{mM}^{jK}\frac{\lambda_{mM}}{\lambda_{iK}}\left(\frac{1}{N_K}\psi_{jK}^{iK}-\delta_{jK}^{kK}\psi_{jK}^{iK}\right),$$

$$\frac{d\log\lambda_{iK}}{d\log z_{kK}} = \alpha(1-\alpha)(1-\rho)\sum_{j\in N_K}\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\Phi_{mM}^{jK}\frac{\lambda_{mM}}{\lambda_{iK}}\left(\frac{1}{N_K}\left(\delta_{jK}^{iK}+\frac{1}{N_K}\beta_K^K\right)-\delta_{jK}^{kK}\left(\delta_{jK}^{iK}+\frac{1}{N_K}\beta_K^K\right)\right),$$

$$\frac{d\log\lambda_{iK}}{d\log z_{kK}} = \alpha(1-\alpha)(1-\rho)\frac{1}{N_K}\left(\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\frac{\lambda_{mM}}{\lambda_{iK}}\frac{1}{N_K}-\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\frac{\lambda_{mM}}{\lambda_{iK}}\delta_{kK}^{iK}\right),$$

$$\frac{d\log\lambda_{iK}}{d\log z_{kK}} = \alpha(1-\alpha)(1-\rho)\frac{1}{N_K}\left(\sum_{M\in N}\sum_{m\in N_M}\omega_M^K\frac{\lambda_{mM}}{\lambda_{iK}}\right)\left(\frac{1}{N_K}-\delta_{kK}^{iK}\right).$$

Substituting the above equation into Equation (C.22), yields:

$$\Delta\log TC_{iK}\approx\alpha(1-\rho)\frac{1}{N_K}\left(\sum_{M\in N}\sum_{m\in N_M}(1-\alpha)\omega_M^K\frac{\lambda_{mM}}{\lambda_{iK}}\right)\left(\frac{1}{N_K}\sum_{k\in N_K}\Delta\log z_{kK}-\Delta\log z_{kK}\right).$$

Denoting by $\mathbb{E}[\Delta\log z_{kK}]=\frac{1}{N_K}\sum_{k\in N_K}\Delta\log z_{kK}$, and writing the above equation in terms of ς_{iK}, we get

$$\Delta\log TC_{iK}\approx(\rho-1)\alpha\varsigma_{iK}\left(\Delta\log z_{iK}-\mathbb{E}[\Delta\log z_{kK}]\right).$$

■

D Additional details on the macroeconomic effects of multisourcing

In this appendix, we provide additional details on the data used in the quantitative exercise in Section 4.4, as well as further information on how we calibrate Equations (26) and (27) from the main text.

Aggregate data, capital shares, and consumption shares. We use the BEA's Integrated Industry-Level Production Account (KLEMS) for time series data on aggregate capital, intermediate goods, and value-added shares in gross output. Combined with quarterly Compustat data, the KLEMS dataset allows us to construct capital stock measures at the 5-digit FIPS level (discussed below), which we use to compute the shocks required to estimate ρ in Equation (28). We also use this data to calibrate the capital share in Equation (26), setting $\alpha = 0.39$ for all periods, which is the average capital share in the US from 1978 to 2017. We set the consumption share θ equal to the inverse of the number of firms in Compustat in each quarter, assuming each firm has an equal weight in final demand.

Natural disaster data and county-level data. To estimate the model, we compute capital-augmenting shocks using data on nominal damages from EM-DAT and county-level estimates of economic activity from the BEA. We first estimate 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).[9] We compute the county-level shock by dividing nominal FIPS-level damages by our estimate of the county's capital stock. FIPS-level damages are measured as the total value of damages caused by *all* natural disasters hitting a particular five-digit FIPS code in a given quarter. More specifically, we first compute the FIPS-level damage for a *given* natural disaster as the total damage caused by that disaster divided by the number of counties affected. Then, to estimate the 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 total costs. We use two measures of firms' total costs. First, our benchmark estimates use information on firms' operating income before depreciation from Compustat and a measure of depreciation to measure firms' profits. Specifically, the rate of depreciation δ_t 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). Each firm's profits are then computed as *operating income before*

[9] 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.

depreciation $\times(1-\delta_t)$. Total costs are then given by nominal sales in the quarter less firm profits: $TC_{iI,t} = Sales_{iI,t} - Profits_{iI,t}$.

Our second measure assumes that firms' operating surplus is equal to firms' payments to capital plus rents from markups. It thus requires estimating each firm's capital stock and the user-cost of capital. To construct firm-level capital stocks, 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 $r_t \times k_{iI,t}$, where r_t is the user-cost of capital in period t, and $k_{iI,t}$ is the sum of the book value of property, plant, and equipment and intangible capital. We follow De Loecker et al. (2020) to measure the user cost of capital as

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

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. As robustness, we also use an alternative measure of the user cost, given by

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

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 that used to calculate firm profits above, and $\mathbb{E}[\Pi_{t+1}]$ 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*). Firms' total costs are then given by the difference between quarterly sales and operating income after depreciation and payments to capital: $TC_{iI,t} = Sales_{iI,t} - Operating\ Income\ (After\ Depr.)_{iI,t} - r_t k_{iI,t}$.

Sector-level input-output matrices. To construct the quarterly sector-level input-output tables, we use inter-firm transactions data from Compustat and estimates of firms' total costs. Omitting time subscripts to reduce notation, the IJ^{th} element of the sector-level input-output matrix is given by

$$\Omega_I^J = \frac{\sum_{i \in N_I} \text{Expenditure on intermediates}_{iI}^J}{\sum_{i \in N_I} TC_{iI}}.$$

where I and J index 6-digit NAICS industries, $\textit{Expenditure on intermediates}_{iI}^{J}$ is firm iI's total expenditure on inputs from firms in industry J and TC_{iI} is iI's total costs. Ω_I^J is therefore equal to industry I's total expenditure on intermediate inputs from J as a share of I's total costs. Firm-level transactions data is from Compustat's *Customer Segments* files and total costs are calculated as above.

To estimate the β's in Equation (26), we compute sector-level Leontief inverse matrices ($\tilde{\mathbf{\Psi}}$) as

$$\tilde{\mathbf{\Psi}} = \left(\mathbf{I} - \tilde{\mathbf{\Omega}}\right)^{-1},$$

where $\tilde{\mathbf{\Omega}}$ is the $N \times N$ sector-level input-output matrix. The elements of $\tilde{\mathbf{\Psi}}$ are the β's.

We also use the industry-level input-output matrices to compute the ς_{iK}'s in Equation (28). Specifically

$$\varsigma_{iK} = \frac{1}{N_K} \sum_{M \in N} \Omega_M^K \frac{\sum_{m \in N_M} TC_{mM}}{TC_{iK}},$$

where Ω_M^K is the MK^{th} element of the matrix $\tilde{\mathbf{\Omega}}$ and TC_{mM} (TC_{iK}) is the total cost of firm mM (iK), computed as above.