Building Corporate Resilience to Specialized Input Disruptions

Leandro Sanz*

July 25, 2025

Abstract

I examine the risk that supply chain disruptions adversely affect firm production and how firms protect themselves against this risk ex ante. Using a new dataset with over 11,000 foreign suppliers to U.S. manufacturers, I show that exposure to this risk depends on input specialization and firms' ability to replace suppliers after shocks. I then provide causal evidence that, to mitigate this risk, firms trade financial flexibility for corporate resilience by increasing inventories, reducing cash, and increasing leverage. As expected from theory, suppliers bear some of this risk for high-bargaining power firms, and firms incur real costs building corporate resilience.

JEL Codes: G31, G32, F23, L23

Keywords: Production networks; global supply chains; corporate resilience

*University of Notre Dame, Mendoza College of Business, Notre Dame, IN 46556. Email: lsanz@nd.edu. I am deeply grateful for the invaluable guidance and support of my committee: Isil Erel, Rüdiger Fahlenbrach, René Stulz, and Michael Wittry. I also thank Kenneth Ahern (discussant), Taylor Begley, Itzhak Ben-David, Daniel Carvalho, Nuri Ersahin (discussant), Kayla Freeman (discussant), Janet Gao (discussant), Gerard Hoberg, Maria Marchica (discussant), Holger Mueller, Mikael Paaso (discussant), Sergio Salgado, Luke Taylor, Alireza Tahbaz-Salehi, Andrea Vedolin, Michael Weisbach, Yufeng Wu, Lu Zhang, and seminar participants at the 9th Annual Marshall PhD Conference in Finance, the 2023 EFA Doctoral Tutorial, the Nova SBE Finance PhD Final Countdown, the 2023 FMA Doctoral Consortium, the 2023 Rising Scholars Conference held at MIT, the 36th Australasian Finance and Banking conference, the 2024 AFA Annual Meeting, the 2024 Eastern Finance Association Annual Meeting, the 2024 NFA Annual Meeting, the 2025 SFS Cavalcade North America, the Ohio State University, the University of Southern California, the University of Pennsylvania, the University of Kentucky, Pennsylvania State University, Indiana University, Washington University in St. Louis, the University of Notre Dame, and Boston University for valuable comments and suggestions. All errors are my own.

1 Introduction

While global supply chains offer well-documented benefits, they expose firms to production disruptions due to policy changes, geopolitical events, natural disasters, and other shocks. Much of the existing literature focuses on the ex post consequences of these shocks (e.g., Barrot and Sauvagnat, 2016; Boehm, Flaaen, and Pandalai-Nayar, 2019), or how supply chain linkages amplify aggregate fluctuations (e.g., Gabaix, 2011; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012). We know much less about the impact of supply chain risk on firms ex ante. Understanding how firms build corporate resilience to supply chain risks has become increasingly important, particularly since firms cannot easily hedge these risks with financial instruments (Brunnermeier, 2024; Stulz, 2024). In this paper, I introduce the concept of "supply chain fragility" to capture the ex ante risk that supplier shocks will adversely affect firm production and show that input specialization is a key determinant of this risk for U.S. manufacturing firms. I then develop a theoretical framework and employ natural experiments to document how firms manage this risk by trading off financial flexibility for corporate resilience, how they share this risk with their suppliers, and the real implications of investing in corporate resilience.

I begin the analysis by constructing a new dataset on the global supply chains of publicly listed U.S. manufacturing firms from 2007 to 2019. The data are derived from administrative bill of lading (BOL) documents collected by the U.S. Department of Homeland Security, Bureau of Customs and Border Protection (CBP). These data provide comprehensive daily information on the maritime import activities of U.S. firms. The granularity and breadth of the BOL data offer a distinct advantage over datasets that use financial reports to infer customer-supplier relationships. Financial reports often omit details on the nature of sourced inputs and tend to skew the inferred relationships in favor of smaller suppliers to larger customers (Carvalho and Tahbaz-Salehi, 2022). Importantly, I validate the quality of the BOL data with other data sources and show that the maritime supply chains characterized by the BOL data are likely an accurate representation of firms' overall global supply chains.

I use these data and two sets of natural experiments, a series of floods at suppliers' locations and tariff increases at the product level, to examine the fragility of U.S. manufacturing firms' supply chains. Specifically, I examine firms' ability to sustain production through these shocks by substituting across suppliers and how this ability varies with input characteristics and the structure of the global input-supplier network. I obtain data from over 2,000 flood incidents from the University of Colorado's Dartmouth Flood Observatory (DFO) and classify a firm-supplier pair as treated if the firm imported from a flood-affected supplier at any time in the five years before the flood. Data on the products targeted by the U.S. tariffs on Chinese goods during 2018 and 2019 at the Harmonized System (HS) code level are obtained from the U.S. International Trade Commission (USTC). These tariffs affected 7,210 products across four waves, with a median tariff increase of 25%. For these shocks, I consider a firm-supplier pair as treated if the firm imported an affected product from a Chinese supplier in the five years before a tariff wave. For both floods and tariffs, control firm-supplier pairs are matched to treated ones on two-digit SIC codes and the pre-treatment log of assets and aggregate import volume at the firm level.

Examining both floods and tariff shocks is useful because firms might respond differently to temporary supply chain disruptions than persistent ones. For example, given the significant fixed costs associated with establishing new supply chain relationships (Antràs, 2003; Antràs, Fort, and Tintelnot, 2017), firms may be more likely to substitute suppliers only when facing persistent shocks. However, these shocks also differ in their nature. While tariffs increase the cost of importing rather than shutting down access to inputs as floods do, one would still expect firms to substitute suppliers if the marginal cost of paying tariffs exceeds switching costs and firms operate in a competitive market with downward-sloping demand.

Using stacked difference-in-differences Poisson pseudo-maximum likelihood (PPML) regressions that estimate treatment effects from variation within each flood and tariff wave (Gormley and Matsa, 2011; Cengiz, Dube, Lindner, and Zipperer, 2019; Baker, Larcker, and Wang, 2022), I find that shipments from affected suppliers decrease by 37% in the four weeks after floods and by 39% in the six months following tariff hikes. However, these effects are highly heterogeneous with respect to input type. For specialized suppliers, whose products are available from only a few other suppliers globally, the decrease is 73% in the four weeks after floods and 61% in the six months after tariffs. The substantial decrease in imports in response to tariff hikes suggests that higher input costs reduce production levels, whether through lower consumer demand when costs are passed through to final prices or through other frictions that limit firms' ability to maintain production at higher input costs. In contrast, firms largely maintain their pre-shock level of input flows during both floods and tariff hikes when the disrupted inputs are generic.

These patterns are driven by firms' ability to reallocate input demand after disruptions. Specifically, firms struggle to substitute specialized suppliers after a shock but can fully reallocate the sourcing of generic inputs through the formation of new supplier relationships. Overall, these findings suggest that shocks to suppliers of specialized inputs are a key driver of supply chain fragility, consistent with recent supply network formation models that show how ex ante disruption risk interacts with input and supplier characteristics to amplify production losses (Oberfield, 2018; Acemoglu and Azar, 2020; Acemoglu and Tahbaz-Salehi, 2020; Elliott, Golub, and Leduc, 2022).

Motivated by these findings, I incorporate supply chain fragility into a standard investment model with financing frictions and examine how firms build corporate resilience to it. In the model, the firm uses both generic and specialized inputs to produce. The key friction is that generic inputs are readily available in the spot market, while specialized inputs lack a spot market following disruptions. The supply chain is fragile in that the suppliers of specialized inputs can be disrupted with positive probability ex ante. The firm finances input purchases with interim cash flows, cash reserves, and external finance and is subject to cash flow shocks.[1] The firm also faces financing frictions when issuing debt, including financing costs and debt capacity constraints.

The model's key result is that, as supply chain fragility increases, firms optimally shift resources from cash into inventories. This reallocation reflects a change in the marginal benefit of holding cash versus inventories. Specifically, increased fragility reduces the marginal value of cash because it cannot be used to purchase specialized inputs on the spot market during disruptions. On the other hand, holding inventories of specialized inputs ensures the firm's operational continuity and cash flow generation during disruptions, making inventories more effective in dealing with this source of supply chain risk ex ante. Cash, nonetheless, remains helpful in mitigating the effects of broader liquidity shocks so that cash balances do not drop to zero. Moreover, because inventories increase convexly with fragility while cash balances fall linearly, there is a financing gap between new input purchases for inventories and freed-up cash, except for low levels of fragility. Therefore, financial leverage increases to cover this gap.

To bridge the theory and empirics, I decompose the model's ex ante fragility parameter into

[1] External financing in the model focuses on debt rather than equity because of its key role in funding input purchases and inventory accumulation (Rajan and Zingales, 1995; Barrot, 2016; Yang and Birge, 2018).

two components. The first component is a function of the characteristics of the supply chain that contribute to its fragility, such as the scarcity of suppliers for specialized inputs. The second component represents the expected probability of disruptions within the supply chain, which firms form based on observed supply chain shocks and their impact on production. I first assume that this expected probability is constant across firms and estimate the effect of supply chain fragility on inventories, cash, and book leverage from variation in the firm-level, import volume-weighted average scarcity of suppliers across a firm's inputs. Given that supplier scarcity tends to be highly persistent within firms, I interpret this measure as an ex ante proxy of supply chain fragility and focus on cross-sectional differences across firms within industries rather than within-firm variation over time. Consistent with the model's predictions, I find that a one standard deviation increase in supplier scarcity is associated with a 9.9% higher input inventory holdings, 12.8% lower cash holdings, and 7.8% higher book leverage relative to their mean values.

I corroborate these results in several ways. First, the relationship between supplier scarcity and book leverage is primarily driven by higher accounts payable, including trade credit, and a greater use of revolving credit facilities, consistent with firms using short-term financing to build inventories. Second, I interact the supplier scarcity measure with a measure of the importance of foreign suppliers compared to domestic suppliers in firms' overall supply chains. This interaction is insignificant, and the coefficient on supplier scarcity remains virtually unchanged, suggesting that supplier scarcity captures an inherent feature of the production process that applies to both domestic and foreign sourcing of inputs. Third, I show that supplier scarcity is positively correlated with discussions of supply chain risk in firms' financial disclosures. Fourth, the findings are robust when using other proxies for fragility, such as the import share of intermediate goods, specialized electronics and scarce raw materials, and the complexity of a firm's input bundle, which recent models have also highlighted as another factor potentially affecting firm's sensitivity to supply chain disruptions (e.g., Elliott, Golub, and Leduc, 2022).

While the results derived from cross-sectional variation are consistent with the model's predictions, they could be driven by unobserved characteristics about production technologies or management that influence both supply chain fragility and financial policies. To establish a causal interpretation, I use supplier floods as exogenous shocks to perceived fragility and investigate how firms adjust their corporate policies in response to these shocks. For these tests, I focus specifically on floods affecting specialized suppliers because these disruptions align more closely with the supply chain fragility captured by the model.

Supply chain shocks provide exogenous variation to identify the effect of ex ante supply chain fragility on corporate policies through a learning or salience mechanism. When a flood unexpectedly disrupts a supplier, managers receive a signal about their supply chain risk and update their beliefs about the general likelihood of such shocks and the nature of their supply chain technology (e.g., the difficulty in replacing specialized inputs). Models of experience-based learning and salience suggest that this update in beliefs will be most intense immediately following a shock and will gradually diminish over time (Malmendier and Nagel, 2011, 2016; Bordalo, Gennaioli, and Shleifer, 2012, 2013). Therefore, I examine changes in imports, inventories, cash holdings, and book leverage over a five-year window around these shocks. Focusing on long-term changes makes it unlikely that the estimated effects are driven by short-term responses to the shocks themselves rather than by belief updates, as the length of the median flood is just seven days.

Using the stacked difference-in-differences approach with a firm-flood-quarter panel, I find that firms increase input inventories by 23%, decrease cash holdings by 21%, and increase book leverage by 19% in the five years after floods. Consistent with higher inventory holdings, imports from affected suppliers increase by 44% over the same period. These effects taper off within the five-year window, suggesting that firms reach an optimal level of inventories, which is consistent with the comparative statics of the model.

The learning and salience channels further suggest that these adjustments should be more pronounced for managers who have experienced a greater number or more recent supply chain disruptions. To test these channels, I allow the estimated treatment effects to vary according to the number of past supplier floods, which serves as a proxy for accumulated information about fragility, and the number of quarters since the most recent flood, which captures the decay of salience. The results show that each additional previous flood intensifies the post-shock increase in shipments and inventories, while the number of quarters since the last flood diminishes this effect. Thus, the evidence supports the idea that firms revise their beliefs about supply chain risk following a shock and adjust their corporate policies accordingly, with the magnitude of these adjustments influenced by experience and recency.

The adoption of inventory buildup as a resilience strategy has important implications for supplier-customer relationships. The sustained increase in shipments and inventories that firms undertake to build corporate resilience against fragility suggests that these shocks could impose physical capacity constraints on suppliers beyond the initial shock. Consequently, suppliers may have to ration their output among customers.[2] Bargaining and hold-up theories suggest that this rationing will favor buyers who account for a significant portion of the supplier's sales or place large orders (Klein, Crawford, and Alchian, 1978; Grossman and Hart, 1986; Antràs and Helpman, 2004; Bimpikis, Candogan, and Ehsani, 2019). In addition, suppliers may shift risk onto themselves by maintaining buffer stocks for priority customers and providing them preferential treatment when production resumes after disruptions, effectively shortening the inventory gap for such customers.

Empirically, the increase in shipments and inventories after a flood is smaller for firms that are the largest customers of their suppliers before the shock and for those that typically place large orders. These findings are consistent with bargaining theories and recent evidence showing that large customers receive preferential treatment from their suppliers (Franzoni, Giannetti, and Tubaldi, 2024). Thus, firms with greater bargaining power can leverage privileged access to inputs during disruptions and save on stockpiling costs. In contrast, less influential firms must build larger inventory stocks to ensure corporate resilience when their supply chains are fragile.

Finally, the inventories firms maintain to increase corporate resilience are costly. Annual holding costs can approach 30% of inventory value (e.g., Ramey, 1989), and the financial resources allocated to increasing inventories are resources that the firm cannot use for investment or innovation. Additionally, lower liquidity and higher leverage increase the shadow cost of external finance, further constraining investment policy (Almeida, Campello, and Weisbach, 2001). These combined forces suggest that building corporate resilience against specialized input disruptions may come at the expense of real activity. Consistent with this tradeoff, my long-horizon estimates show that firms experience higher operating costs, lower profit margins, lower physical investment and innovation, and lower shareholder payouts as they build corporate resilience to supply chain fragility.

This paper contributes to several streams of literature. First, it builds on recent theoretical

[2] Suppliers could, in principle, also raise prices to clear markets during a shock. In practice, however, capacity constraints often bind first. For example, U.S. importers received sharply fewer shipments from Japanese plants with almost no offsetting price increase after the 2011 Tōhoku earthquake, suggesting that quantities were the primary margin of adjustment during the shock (Boehm, Flaaen, and Pandalai-Nayar, 2019). Additionally, suppliers may prefer rationing to preserve long-term relationships with key customers rather than risk damaging these relationships through opportunistic pricing during shortages (Macchiavello and Morjaria, 2015).

work on how firms might mitigate risks in their production networks through intensive (Bimpikis, Candogan, and Ehsani, 2019; Acemoglu and Azar, 2020) and extensive margin adjustments (Acemoglu and Tahbaz-Salehi, 2020; Elliott, Golub, and Leduc, 2022; Kopytov, Mishra, Nimark, and Tascherau-Dumouchel, 2024). Recent studies have found empirical evidence that firms use the restructuring channel to mitigate supply chain risk (Ersahin, Giannetti, and Huang, 2024a; Khana, Morales, and Pandalai-Nayar, 2022; Pankratz and Schiller, 2025) and that there is risk-sharing between suppliers and customers through the use of trade credit (Ersahin, Giannetti, and Huang, 2024b). In contrast, I focus on supply chain fragility that stems from specialized inputs that are hard to substitute across suppliers. Constructing a new transaction-level dataset of U.S. manufacturing firms' global supply chains, I show that firms build corporate resilience and self-insure against this risk by increasing input sourcing and maintaining large inventory stocks. In addition, I show that firms sacrifice financial flexibility in doing so, and that these tradeoffs have adverse real effects on profitability, investment, innovation, and payouts.

Second, my research contributes to the literature on the tradeoffs between financial and operational hedging. While firms can use derivative contracts and insurance to hedge their risk exposures and reduce the underinvestment problem caused by costly external financing (Smith and Stulz, 1985; Froot, Scharfstein, and Stein, 1993), market frictions often make operational hedging a complement or substitute for financial hedging. For example, offshore activities can be an operational hedge against foreign exchange risk when derivative markets are illiquid or incomplete (Allayannis, Ihrig, and Weston, 2004; Hoberg and Moon, 2017). In a contemporaneous paper, Acharya, Almeida, Amihud, and Liu (2025) develop a model in which financially constrained firms substitute between financial and operational hedging. Their model predicts that financially weaker firms preserve cash by cutting operational hedges, which lowers costs and widens markups. Empirically, they show that higher default risk is associated with larger gross-profit margins, lower inventories to sales ratios, and less supplier diversification, with these effects more pronounced when credit supply tightens. Rather than examining how financial constraints affect operational hedging decisions, I focus on the risk of fragile supply chains that arises because specialized inputs cannot be sourced on a spot market after disruptions, even when firms have ample financial resources. Exploiting exogenous shocks to suppliers of specialized inputs, I show that managers update their beliefs about supply chain fragility after such shocks and adjust their input inventory stocks, cash holdings, and leverage to build corporate resilience. Moreover, I show that firms with high bargaining power engage in less operational hedging because they share supply chain risk with suppliers.

My research also contributes to the literature on the joint evolution of corporate cash holdings and inventories. It is well-documented that cash ratios have increased significantly since the early 2000s while inventories have declined. These trends can be partly attributed to changes in firm characteristics, such as production and inventory technologies (e.g., Bates, Kahle, and Stulz, 2009; Denis, 2011; DeAngelo, Gonçalves, and Stulz, 2018; Graham and Leary, 2018; Begenau and Palazzo, 2021; Falato, Kadyrzhanova, Sim, and Steri, 2022). Additionally, Kulchania and Thomas (2017) link the secular increase in cash and the decrease in inventories to supply chain risk. They suggest that firms with low inventory levels face higher disruption costs, prompting them to accumulate cash reserves that they can draw upon in the event of a shock. By contrast, my findings indicate that the substitution between cash and inventories occurs in both directions. Because specialized inputs have no spot market during disruptions, firms use cash and debt to build inventories in anticipation of shocks. Furthermore, my model predicts that cash holdings are effective in mitigating supply chain risk for generic inputs. Because these inputs remain available in spot markets during disruptions, firms can draw down their cash reserves and procure these inputs as needed.

Lastly, my research contributes to the literature on the risks and benefits of multinational operations. Multinational corporations (MNCs) benefit from diversified financing options across multiple capital markets (Jang, 2017), but they also face unique risks, including political uncertainty, expropriation risk, and foreign exchange risk (Desai, Foley, and Hines, 2008; Lin, Mihov, and Sanz, 2019; Dominguez and Tesar, 2008). In addition, sunk costs in foreign investments can limit diversification benefits and heighten cashflow comovement with global shocks (Melitz, 2003; Fillat and Garetto, 2015; Fillat, Garetto, and Oldenski, 2015). By examining the risks that arise from sourcing inputs through fragile supply chains, my study introduces a new perspective to the ongoing discussion. It emphasizes that, in addition to the general risks associated with multinational operations, the global sourcing of specialized inputs can present significant challenges for firms.

2 Global supply chains, specialized inputs, and disruptions

This section describes the sample construction, the global supply chains data, and other data used in the empirical analysis.

2.1 Sample construction

The sample begins with a list of U.S. publicly listed manufacturing firms (SIC codes 2000–3999) in Compustat from Q1 2007 to Q4 2019. I restrict the sample to Q4 2019 to avoid confounding effects from supply chain disruptions during the COVID-19 pandemic. Firms are required to have non-missing total assets and sales, as well as at least three years of consecutive data, resulting in 2,346 manufacturing firms. From this set, the study focuses on 923 firms with global supply chains, defined as firms that import from foreign suppliers. Import data is obtained from Panjiva, which provides granular data on U.S. maritime imports derived from bill of lading (BOL) documents, including product descriptions, supplier identifiers, and logistical details such as ports and shipping vessels.[3] I focus on three measures of import intensity: shipment counts, import weight, and import volume (measured in TEUs, the volume of a standard cargo container). For each import, I consider the supplier to be the ultimate parent of the supplier recorded in the BOL form.

In addition to data on global supply chains, I obtain financial data from Compustat and Capital IQ, equity data from the Center for Research in Security Prices (CRSP), data on natural disasters from the Dartmouth Flood Observatory at the University of Colorado, and data on the 2018-2019 U.S. import tariffs from the U.S. International Trade Commission (USTC).

2.2 BOL data global supply chains

Flaaen, Haberkorn, Lewis, Monken, Pierce, Rhodes, and Yi (2023) compare the BOL data to aggregate data on containerized vessel import value and confidential administrative datasets from the U.S. Census Bureau. They show that the BOL data is highly consistent with the U.S. Census Bureau's data while often providing greater granularity on firms' inputs and suppliers. However, a limitation of the BOL data is that it does not cover non-maritime trade.

Internet Appendix A examines the representativeness of global supply chains constructed from

[3] Internet Appendix A includes an example of a BOL form.

the BOL data by analyzing the share of U.S. imports transported via maritime shipments. I show that, by both weight and value, maritime shipments are the predominant mode of transportation. Although certain products, such as pharmaceuticals, primarily rely on air transport, pharmaceutical manufacturing firms account for only about 7% of the sample. Moreover, many specialized products, including electrical equipment and machinery, are well represented in both maritime and air imports. For example, each of these categories makes up roughly one-third of the top ten HS codes for each mode of transport. These findings suggest that the characteristics of firms' global supply chains, as derived from BOL data, are likely representative of their overall supply chains.

Internet Appendix A also presents several stylized facts about U.S. manufacturing firms' global supply chains. First, imports predominantly consist of raw materials and intermediate goods (collectively referred to as inputs) rather than finished products. Second, there is a significant concentration of suppliers in certain countries. For example, China accounted for 31% of all suppliers in 2019. Third, Internet Appendix A further highlights the heterogeneity of input-supplier networks. While some inputs are generic and sourced from many suppliers worldwide, many inputs are highly specialized, sometimes available from only a few suppliers or even a single one.

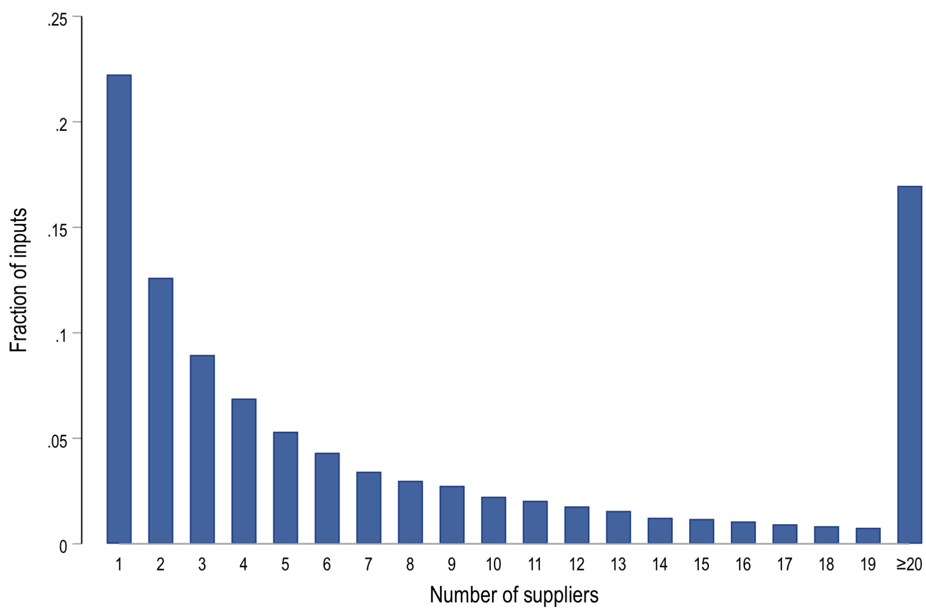
2.3 Specialized inputs

I leverage the detailed input-supplier network in the BOL data to identify specialized inputs. For each input a firm uses, I count the number of alternative suppliers from which other firms source that same input, excluding the firm's current supplier. An input is considered specialized when the number of alternative suppliers is below the sample median of four. This approach broadly captures input specialization without limiting the focus to specific categories, such as semiconductors or high-grade chemicals, and captures supply chain fragility across a wide range of inputs. Figure 1 illustrates this fragility, showing a bimodal distribution in input sourcing. Specifically, a substantial fraction of inputs are highly specialized, with only one or a few suppliers available, while many inputs are generic and available from 20 or more suppliers.

2.4 Supplier floods

I collect detailed data on floods from the Dartmouth Flood Observatory (DFO) at the University of Colorado. The DFO compiles information from various sources, including media reports, gov-

Figure 1: Fraction of inputs by the number of global suppliers
This figure shows the fraction of inputs sourced by firms by the number of suppliers providing those inputs. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019.



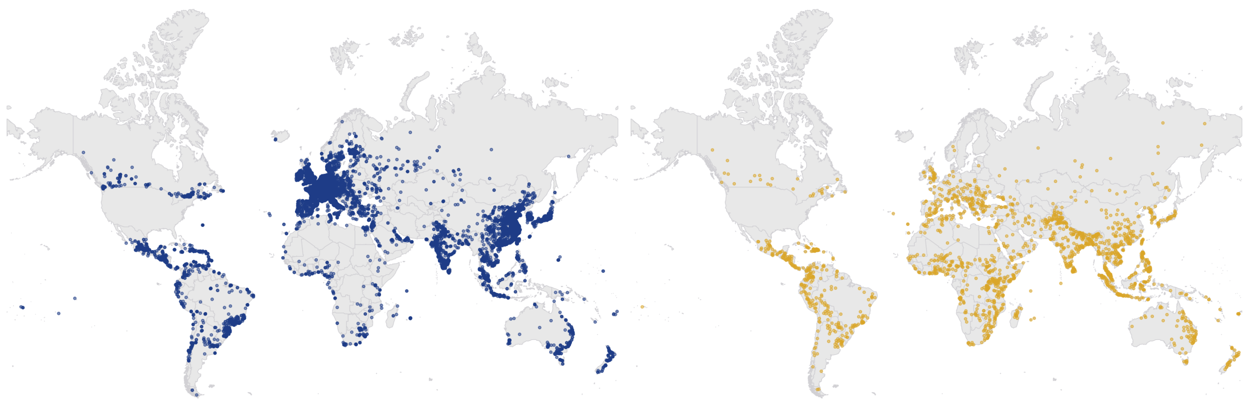
ernmental records, and satellite imagery. For each flood, the dataset provides the start and end dates, the coordinates of the flood's center, the total area affected in square miles, the number of displaced individuals, and the number of casualties. There are 2,122 floods in the data since 2007.

Figure 2 illustrates the geographic distribution of floods and the locations of affected suppliers, highlighting substantial variation in the occurrence of these natural disasters. The floods are not confined to specific regions or periods, reducing concerns that they might coincide with cyclical trade patterns or be limited to particular areas. Major events in the dataset include the March 2011 tsunami in Japan, triggered by the Tōhoku earthquake, and the Thailand floods that occurred later that year. Both events had significant consequences for U.S. manufacturers reliant on Japanese and Thai suppliers. For example, the tsunami caused severe supply chain disruptions (e.g., Boehm, Flaaen, and Pandalai-Nayar, 2019), while the Thailand floods led to the closure of a key Western Digital factory, which had a significant impact on the computer manufacturing industry.[4] Of the 2,122 floods documented in the DFO data, 1,508 impacted the suppliers of the firms in my sample.

[4] See "Thailand flooding cripples hard-drive suppliers," by Thomas Fuller, November 6, 2011, *The New York Times*.

Figure 2: The geographic distribution of suppliers and floods
Panels A and B of this figure show the geographic distribution of foreign suppliers and floods, respectively. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019.

Panel A: Geographic distribution of suppliers **Panel B:** Geographic distribution of floods



2.5 The 2018 and 2019 tariffs on Chinese goods

I collect six-digit HS-code-level data on the 2018 and 2019 U.S. import tariffs on Chinese goods from the USTC. The USTC implemented these tariffs in four waves. The first wave, enacted on July 6, 2018, applied a 25% tariff to 597 products. The second wave, which took effect on August 23, 2018, imposed a 25% tariff on an additional 2,016 products. The third wave, introduced on September 24, 2018, significantly expanded the scope by applying a 10% tariff to 3,248 products.[5] The 10% tariff was increased to 25% on May 5, 2019. The fourth wave, enacted on September 1, 2019, imposed a 15% tariff on 1,349 products. There were also announcements of the tariff schedules that preceded enactment by two to four weeks.

2.6 Descriptive statistics

Table 1 presents descriptive statistics for global supply chains (Panel A), accounting characteristics (Panel B), and floods (Panel C) based on a firm-quarter panel of 923 publicly listed U.S. manufacturing firms from Q1 2007 to Q4 2019. During this period, the median firm received 63 shipments and 85 TEUs quarterly. However, the distribution of imports is notably skewed, with the average firm receiving 278 shipments and 561 TEUs. These firms typically import a diverse range of products from suppliers located in multiple countries each quarter. For example, the median

[5] See Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2020) for a detailed discussion of the 2018 tariffs and their impact on the U.S. economy.

Table 1: Summary Statistics

This table reports summary statistics on global supply chains (Panel A), accounting characteristics (Panel B), and floods. The sample in Panels A and B is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. The sample in Panel C is comprised of the 1508 floods that affect firms in the sample through their suppliers. Appendix A presents variable definitions.

	Obs	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Supply chains						
Import volume (TEU)	31,214	561.27	1,340.52	12.00	85.45	414.62
Number of import countries	31,214	8.72	8.13	3.00	6.00	12.00
Number of products	31,214	22.49	30.23	4.00	11.00	29.00
Number of shipments	31,214	277.89	592.51	13.00	63.00	250.00
Number of suppliers	31,214	24.81	38.48	4.00	11.00	30.00
Panel B: Accounting characteristics						
Assets ($billions)	31,214	5.86	13.32	0.36	1.30	4.38
Cash/Assets	31,214	0.14	0.15	0.04	0.10	0.20
Cash flow/Assets	31,214	0.03	0.04	0.02	0.03	0.04
Capex/Net PP&E	31,207	0.13	0.11	0.05	0.10	0.17
Input inventories/Assets	31,214	0.09	0.08	0.04	0.07	0.12
M/B	31,214	3.02	5.55	1.34	2.19	3.63
R&D/Sales	31,214	0.12	2.70	0.00	0.01	0.06
Total debt/Assets	31,214	0.23	0.19	0.08	0.22	0.35
Panel C: Floods						
Flood length (days)	1,508	12.53	18.28	4.00	7.00	14.00
Number displaced	1,508	84,851.41	534,770.51	0.00	1,000.00	15,000.00
Number of casualties	1,508	112.51	2,597.52	0.00	3.00	17.00
Area affected (sq miles)	1,508	57,580.99	101,017.61	9,453.93	23,963.95	62,223.51

firm procured 11 distinct products from 11 different suppliers across six countries.

Panel B of Table 1 indicates that, from Q1 2007 to Q4 2019, the median total debt and cash-to-asset ratios for sample firms were 22% and 10%, respectively. These firms generally exhibit less financial flexibility than those in the broader Compustat sample, where the median book leverage and cash-to-assets ratios are 15% and 18%, respectively. Moreover, the sample firms tend to be larger, more profitable, and hold more inventories. For example, the median ratio of input inventories to assets is 7% in the sample, compared to zero in the unrestricted dataset.

Panel C of Table 1 provides summary statistics for the flood events. These events affected 16,322 suppliers in 64 countries and impacted 769 firms, or 83% of the firms in the sample at some point. The median flood lasts for seven days, displaces 1,000 individuals, results in three casualties, and affects a total area of 23,963.95 square miles.

3 Specialized supply chains and corporate resilience

This section explains the empirical strategy and examines how specialized inputs contribute to supply chain fragility.

3.1 Empirical strategy

I begin by using difference-in-differences regressions around flood events and tariff waves to examine how supply chain disruptions affect firms' ability to source inputs and maintain production. These events create a staggered treatment setting, with treatment timing varying across firms, and many firms experience multiple shocks. Given that the traditional difference-in-differences estimator can be biased under these conditions (e.g., Goodman-Bacon, 2021), I adopt a stacked regression approach (Gormley and Matsa, 2011; Cengiz et al., 2019; Deshpande and Li, 2019; Baker, Larcker, and Wang, 2022). This method constructs separate cohorts for each flood and tariff wave event. For floods, a firm-supplier pair is treated if the firm imported from the flood-affected supplier at any time in the five years preceding the flood. Similarly, for tariffs, a firm–supplier pair is treated if the firm imported from the tariff-affected supplier at any point during the five years before a tariff wave. In each cohort, control pairs are defined as those that have not been affected by the current flood or tariff wave and have not been impacted by any prior event. By focusing on clean within-cohort comparisons, this approach reduces the risk of biased treatment effect estimates. The stacked difference-in-differences regression model is specified as follows:

$$Y_{ist} = \alpha_{isj} + \alpha_{tj} + \beta Treated^j_{is} \times Post^j_t + \gamma X_i \times Post^j_t + \epsilon_{ist} \tag{1}$$

where i denotes firms, s suppliers, j flood or tariff events, and t weeks or months. For floods, the model is estimated using a symmetric four-week window around each flood event, with event week 0 corresponding to the first flood week. For tariffs, the model is estimated using a symmetric six-month window around the enactment of each tariff wave. $Treated^j_{is}$ equals one for firm-supplier pairs that are treated as defined above, while $Post^j_i$ equals one during the four weeks or six months following the start of the event. I define the start of each tariff event as the event month before enactment to capture any anticipation effects arising between the announcement and the implementation date. The dependent variable, Y_{ist}, is the number of shipments. $X_i \times Post_t^j$ is a vector firm-level controls measured in the pre-treatment period and interacted with $Post_t^j$, including the log of assets, market-to-book ratios, R&D expenditures over sales, cash flows over assets, and capital expenditures over net property, plant, and equipment. To estimate average treatment effects across events, the main specifications include firm×supplier×event and calendar time×event fixed effects, denoted by α_{isj} and α_{tj}, which absorb the standalone variables $Treated_{is}^j$ and $Post_t^j$. I also consider alternative fixed effects to examine substitution effects across suppliers. In those cases, the treatment variable is defined at the firm level, $Treated_i^j$, and equals one if a firm has at least one affected supplier. Standard errors are clustered at the firm and calendar time levels.

I take two additional steps to refine the identification of treatment effects. First, I balance treated and control firms using a matching approach similar to Bena, Dinc, and Erel (2022). Specifically, I use exact matching on two-digit SIC codes and nearest neighbor matching on the pre-treatment log of assets and aggregate import volume. This ensures that treated and control firms operate in the same industry and exhibit similar pre-treatment scale and importing activity. Second, to account for seasonality, the pre-treatment values of the dependent variable are computed by averaging imports from the same calendar weeks (or months) as the event weeks, using data from the previous three years. For example, for floods, the import value for event week -4 is calculated as the average imports during the calendar week corresponding to the first flood week (event week 0) over the prior three years. This creates a seasonally adjusted benchmark that better captures deviations from typical firm behavior.

3.2 Floods

I estimate Poisson pseudo-maximum likelihood (PPML) regressions of Equation 1 because the weekly and monthly trade data often include zero flows, and the PPML estimator naturally handles these zeros while producing consistent, unbiased estimates (Silva and Tenreyro, 2006). Panel A of Table 2 presents the results for changes in the number of shipments around floods.[6]

Column (1) of Panel A shows that controlling for firm×supplier ×flood and calendar week×flood fixed effects, the number of shipments from flood-affected suppliers decreases by $(e^{-0.464}-1)\times 100 \approx$

[6] I show in Internet Appendix B that the results are consistent under several alternative specifications, including PPML regressions of import volume and OLS regressions using either the log of one plus the number of shipments (or import volume) and the number of shipments (or import volume) scaled by pre-treatment assets.

Table 2: Specialized inputs and supply chain fragility

This table presents results from stacked difference-in-differences regressions of the number of shipments over two distinct event windows: a four-week window around flood events (Panel A) and a six-month window around tariff waves (Panel B). The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q4 2007 to Q4 2019. In Panel A, the data form a firm–supplier–flood event–week panel, while in Panel B, the data form a firm–supplier–tariff wave–month panel. The dependent variable in both panels is the number of shipments. In column (1) of Panel A (B), *Treated* equals one for firm–supplier pairs where the firm imported from a flood- (tariff-) affected supplier at any time in the five years before the event. In columns (2) to (4) of Panels A and B, *Treated* equals one for firms that had at least one treated supplier during the event. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate import volume. The specifications in columns (1) of Panels A and B include firm×supplier×event and calendar time×event fixed effects, whereas columns (2) to (4) replace the firm×supplier×event fixed effects with firm×event fixed effects. Standard errors clustered at the firm and calendar time levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel A: Floods				
	Shipments			
	Firm-supplier pairs	Substitution across suppliers		
	All	All	Specialized	Generic
	(1)	(2)	(3)	(4)
Treated × Post	−0.464***	−0.267***	−1.300***	0.050
	(0.029)	(0.052)	(0.118)	(0.045)
Ln(Assets) × Post	0.018*	0.023**	0.135***	0.004
	(0.009)	(0.010)	(0.036)	(0.008)
M/B × Post	0.001	−0.001	0.002	−0.001
	(0.002)	(0.002)	(0.006)	(0.002)
R&D/Sales × Post	−0.012	−0.014	−2.249*	−0.029
	(0.011)	(0.012)	(1.214)	(0.021)
Cash flow/Assets × Post	−0.081	0.035	−1.743	0.297
	(0.701)	(0.708)	(1.912)	(0.701)
Capex/Net PP&E × Post	0.660***	0.662***	0.305	0.344**
	(0.192)	(0.189)	(0.874)	(0.163)
Fixed effects				
Firm × Supplier × Flood	Yes	No	No	No
Firm × Flood	No	Yes	Yes	Yes
Calendar week × Flood	No	Yes	Yes	Yes
Observations	569,574	569,574	199,413	363,094
Pseudo R^2	0.50	0.30	0.42	0.31

−37% in the four weeks following a flood, relative to the corresponding tree-year pre-treatment mean. This result suggests that even brief supply chain shocks can substantially impact a firm's ability to source inputs from its suppliers. In columns (2) to (4), I investigate whether firms can substitute across suppliers and how that ability depends on input specialization. To do so, I redefine the treatment variable so that it equals one if a firm has at least one flood-affected supplier in a given week, and then replace the firm×supplier×flood fixed effects with firm×flood fixed effects.

Table 2: Specialized inputs and supply chain fragility, continued
This table presents results from stacked difference-in-differences regressions of the number of shipments over two distinct event windows: a four-week window around flood events (Panel A) and a six-month window around tariff waves (Panel B). The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. In Panel A, the data form a firm–supplier–flood event–week panel, while in Panel B, the data form a firm–supplier–tariff wave–month panel. The dependent variable in both panels is the number of shipments. In column (1) of Panel A (B), *Treated* equals one for firm–supplier pairs where the firm imported from a flood- (tariff-) affected supplier at any time in the five years before the event. In columns (2) to (4) of Panels A and B, *Treated* equals one for firms that had at least one treated supplier during the event. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate import volume. The specifications in columns (1) of Panels A and B include firm×supplier×event and calendar time×event fixed effects, whereas columns (2) to (4) replace the firm×supplier×event fixed effects with firm×event fixed effects. Standard errors clustered at the firm and calendar time levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel B: Tariffs				
	Shipments			
	Firm-supplier pairs	Substitution across suppliers		
	All	All	Specialized	Generic
	(1)	(2)	(3)	(4)
Treated × Post	−0.501***	−0.839**	−0.950**	0.199
	(0.075)	(0.368)	(0.370)	(0.206)
Ln(Assets) × Post	0.050	0.060**	0.105***	−0.029
	(0.032)	(0.030)	(0.028)	(0.043)
M/B × Post	0.023	0.018	0.009	0.042*
	(0.016)	(0.015)	(0.012)	(0.023)
R&D/Sales × Post	−0.014	0.006	0.012	−0.087
	(0.046)	(0.044)	(0.036)	(0.287)
Cash flow/Assets × Post	3.318	3.340	2.692	4.643
	(3.071)	(2.840)	(2.328)	(4.149)
Capx/Net PP&E × Post	1.318**	0.974*	1.256	0.534
	(0.573)	(0.572)	(0.884)	(0.626)
Fixed effects				
Firm × Supplier × Tariff wave	Yes	No	No	No
Firm × Tariff wave	No	Yes	Yes	Yes
Calendar month × Tariff wave	No	Yes	Yes	Yes
Observations	482,857	482,857	299,370	183,487
Pseudo R^2	0.65	0.20	0.22	0.27

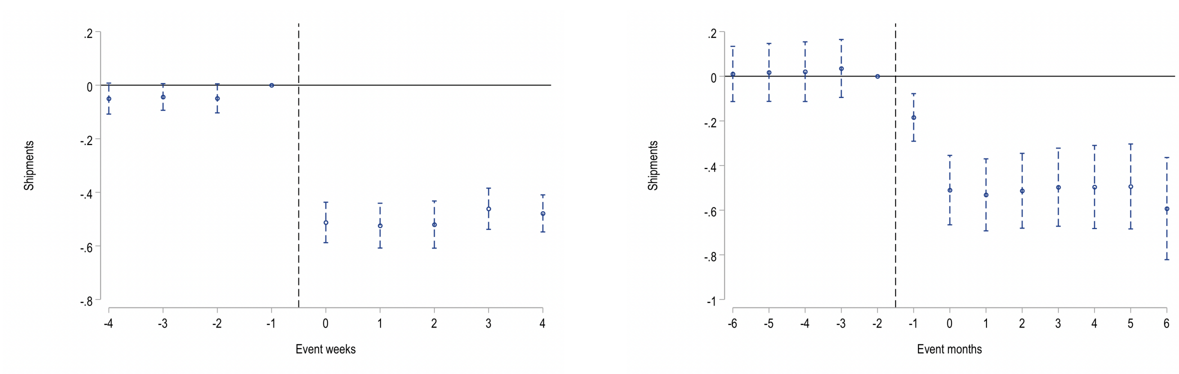
As a result, $Treated \times Post$ now captures the pooled treatment effect on that firm's total imports when the firm has at least one affected supplier. Column (2) includes all suppliers, while columns (3) and (4) split the sample into specialized and generic suppliers. I classify suppliers as specialized if they provide at least one input for which the total number of global suppliers is below the sample median. All other suppliers are classified as generic.

The result in column (2) is smaller than that of column (1), suggesting that, on average, firms

Figure 3: Supply chain fragility event study

This figure plots the β coefficients and 95% confidence intervals from event study regressions based on a specification analogous to Equation 1: $Y_{ist} = \alpha_{isj} + \alpha_{tj} + \beta_{t=-k}^{t=k} Treated_{is}^{j} \times Event\ time_{t}^{j} + \gamma X_i \times Post_{t}^{j} + \epsilon_{ist}$, where i denotes firms, s suppliers, j flood or tariff events, and t weeks or months. Y_{ist} is the number of shipments. In Panel A, $Treated_{is}^{j}$ equals one for firm-supplier pairs where the firm imported from the flood-affected supplier at any time in the five years preceding the flood, and $Event\ time_{t}^{j}$ is a vector of indicator variables for event weeks -4 through $+4$. In Panel B, $Treated_{is}^{j}$ equals one for firm-supplier pairs where the firm imported from the tariff-affected supplier at any time in the five years before the tariffs took effect, and $Event\ time_{t}^{j}$ is a vector of indicator variables for event months -6 through $+6$. $X_i \times Post_{t}^{j}$ is a vector of firm-level controls, including the log of assets, market-to-book ratios, R&D expenditures over sales, cash flows over assets, and capital expenditures over net property plant and equipment measured in the pre-treatment quarter, interacted with $Post_{t}^{j}$, an indicator variable that equals one during the weeks or months following the start of the event. α_{isj} and α_{ij} denote firm×supplier×event and calendar time×event fixed effects, respectively. Standard errors are clustered at the firm level.

Panel A: Floods **Panel B:** Tariffs



partially offset the decrease in shipments after floods by sourcing from other suppliers. However, the results in columns (3) and (4) reveal significant heterogeneity. In column (3), for specialized inputs, the number of shipments by treated firms declines by about 73%. By contrast, column (4) shows that, for generic inputs, the treatment effect is close to zero and statistically insignificant, indicating that firms can fully substitute across suppliers in these cases. Overall, these findings suggest that supply chain fragility and its impact on corporate resilience depend on whether suppliers provide generic or specialized inputs.

Panels A and B of Figure 3 present the event study figures corresponding to column (1) in Panels A and B of Table 2. The figure in Panel A shows that pre-treatment differences in the number of shipments between treated and control firm–supplier pairs are close to zero and statistically insignificant at the 5% level. They also document a sudden and persistent decline in shipments over the four-week event window.

3.3 Tariffs

It is possible that only persistent disruptions trigger changes in supply networks, given the large fixed costs associated with establishing new supply chain relationships (Antràs, 2003; Antràs, Fort, and Tintelnot, 2017). If so, the previous findings may overstate the lack of supplier substitution for specialized inputs. To explore this possibility, this section examines supply chain fragility and supplier churn during the prolonged shock of the 2018 and 2019 import tariffs on Chinese goods.

The staggered introduction of these tariffs provides a natural experiment for examining how a prolonged policy shock affects supplier reallocation, for two main reasons. First, the median tariff increase across the waves was 25%, a substantial increase given that many of the targeted goods had been tariff-free prior to 2018. Second, to the extent that President Trump's 2016 election was unexpected, and firms could not predict which goods would be included in future waves, these tariffs can be considered plausibly exogenous (Amiti, Redding, and Weinstein, 2019). This exogeneity helps mitigate the concern that tariff hikes typically coincide with underlying demand and supply shocks (Fajgelbaum et al., 2020).

Although the tariffs do not constitute a complete supply chain disruption as floods do, they create persistent cost increases. In a competitive market with downward-sloping demand, these higher costs should lead to fewer imports. Moreover, if the marginal cost of paying the tariff on Chinese goods exceeds the fixed cost of switching, one would expect firms to source inputs from suppliers outside of China. For specialized inputs, however, alternative suppliers may be scarce or require relationship-specific investments, which can make it more difficult for firms to switch.

Panel B of Table 2 presents the PPML-based treatment effect estimates for changes in the number of shipments around the tariff waves.[7] According to column (1), shipments from Chinese suppliers subject to tariffs drop by about $(e^{-0.501} - 1) \times 100 \approx -39\%$ over the six months following each tariff increase. This effect is of the same order of magnitude as those documented by Amiti, Redding, and Weinstein (2019), who estimate an aggregate decrease in the number of imports following the tariff waves of approximately 25-30%.

Columns (2) to (4) of Panel B examine the ability of firms to reallocate imports across suppliers following the tariff hikes. In column (2), the more negative coefficient compared to column (1)

[7] As with floods, I find similar results using alternative specifications. See Internet Appendix B.

indicates that overall imports within the firm decline by more than imports from affected Chinese suppliers on average, suggesting limited substitution and possible spillovers to other inputs sourced from unaffected suppliers. As in Panel A, columns (3) and (4) show that supplier substitution depends on whether inputs are specialized or generic. Specifically, when the tariffed inputs are specialized (column (3)), imports within the firm decrease by about 61%, suggesting firms are unable to replace most imports of specialized inputs with alternative sources. By contrast, the coefficient in column (4) is positive and statistically insignificant for generic inputs, implying that within-firm substitution allows firms to largely maintain their pre-treatment import levels for those inputs. Panel B of Figure 3 presents the event study graph corresponding to column (1). Similar to Panel A, the pre-treatment coefficients are close to zero and statistically insignificant. The figure also shows a modest decline in imports in the month before enactment, followed by a large, persistent decrease throughout the six-month post-treatment window.

Another way to examine substitution effects among generic and specialized inputs after persistent supply chain shocks is to investigate whether firms restructure their supply chains away from affected suppliers and toward those that are not affected. Such supplier churn is likely more challenging for specialized inputs than for generic inputs, given the higher fixed costs associated with relationship-specific investments and the scarcity of suppliers for these types of inputs.

To examine this, I estimate difference-in-differences regressions analogous to Equation 1 on a firm–tariff wave–month panel, separately for suppliers of specialized and generic inputs. The dependent variable in these regressions is *Suspended supplier relationships* or *New supplier relationships*. *Suspended supplier relationships* is equal to one when a firm imported from a supplier in the five years before the pre-treatment window but does not import from that supplier in the post-period. Similarly, *New supplier relationships* is an indicator equal to one when a firm imports from a supplier in the post-period that it did not import from in the five years before the pre-treatment window (i.e., the five years ending at event month –7). Note that, by definition, both variables are zero in the pre-period, so changes in these variables can be interpreted as the net effect of the tariff shock. Table 3 presents the results.

Consistent with the import quantity effects in Table 2, columns (1) and (2) show that tariff enactment increases the suspension probability of imports from existing suppliers by 6.0 percentage points for specialized inputs and by 6.9 percentage points for generic inputs. By contrast, columns

Table 3: Supplier churn

This table presents results from stacked difference-in-differences regressions of supplier churn, the fraction of new and terminated supplier relationships, in a six-month window around tariff waves. The sample consists of a firm-tariff wave-month panel of 923 publicly listed U.S. manufacturing firms with global supply chains from 2007 to 2019. *Suspended supplier relationships* equals one when a firm imported from a supplier in the five years before the pre-treatment window but does not import from that supplier in the post-period. *New supplier relationships* equals one when a firm imports from a supplier in the post-period that it did not import from in the five years before the pre-treatment window. *Treated* equals one for firms that had at least one treated supplier during the event. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. All specifications include firm×event and calendar time×event fixed effects. Standard errors clustered at the firm and calendar time levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Suspended supplier relationships		New supplier relationships	
	Specialized	Generic	Specialized	Generic
	(1)	(2)	(3)	(4)
Treated × Post	0.060***	0.069**	0.001	0.028**
	(0.009)	(0.030)	(0.004)	(0.011)
Ln(Assets) × Post	0.003	0.012**	−0.000	−0.008
	(0.003)	(0.005)	(0.001)	(0.005)
M/B × Post	0.001	−0.003	0.001	0.002
	(0.001)	(0.002)	(0.000)	(0.001)
R&D/Sales × Post	0.002	−0.007	−0.001	−0.008
	(0.003)	(0.005)	(0.001)	(0.006)
Cash flow/Assets × Post	−0.111	0.054	−0.067	−0.462
	(0.177)	(0.258)	(0.072)	(0.403)
Capex/Net PP&E × Post	−0.133**	0.352***	−0.002	−0.101
	(0.050)	(0.112)	(0.018)	(0.106)
Fixed effects				
Firm × Wave	Yes	Yes	Yes	Yes
Calendar month × Wave	Yes	Yes	Yes	Yes
Observations	30,741	30,741	30,741	30,741
Adj. R^2	0.56	0.76	0.36	0.38

(3) and (4) show that firms cannot establish new relationships with suppliers of specialized inputs after the shock but can form new relationships with suppliers of generic inputs. Thus, while supply chain shocks disrupt the sourcing of both input types, firms can only reallocate demand for generic inputs to new suppliers, consistent with the substitution effects in Table 2.

4 Supply chain fragility and investment in corporate resilience

The previous section shows that reliance on specialized inputs can significantly increase supply chain fragility, defined here as the risk that firms will be unable to maintain production following disruptions. To remain operational, firms might invest in corporate resilience, or the capacity to absorb those shocks and recover quickly after them. This section introduces a theoretical framework that links supply chain fragility to firms' corporate policies and provides testable hypotheses about how firms manage those policies to maintain resilience.

4.1 A simple model of supply chain fragility

Following Elliott, Golub, and Leduc (2022), I model supply chain fragility as an inherent characteristic of the production process and the inputs it requires. Specifically, I consider a firm that uses two distinct inputs for production: a generic input, denoted by g, and a specialized input, denoted by s. The generic input is available on the spot market, guaranteeing the firm continuous access to alternative suppliers. By contrast, the specialized input is not procurable on the spot market, either due to a scarcity of potential suppliers or the need for relationship-specific investments.

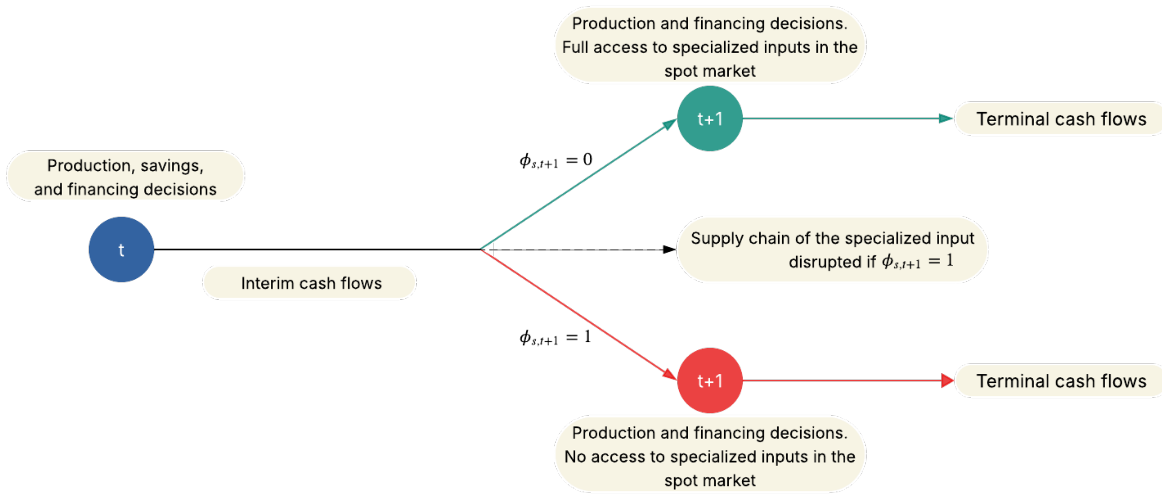
The firm operates over two periods. In the first period, t, it decides on production inputs, inventory levels, cash reserves, and debt financing.[8] In the subsequent period, $t+1$, it determines its production inputs and any additional debt financing needs. At the end of period t, the firm realizes interim cash flows from its production decisions. These interim cash flows, combined with the cash saved from period t, help fund the procurement of production inputs in period $t+1$.

The firm's ability to acquire the specialized input in period $t+1$ depends on the parameter $\phi_{s,t+1}$. When $\phi_{s,t+1} = 1$, the specialized input's supply chain is disrupted before period $t+1$, forcing the firm to rely exclusively on the inventory of specialized inputs it accumulated in period t. Conversely, when $\phi_{s,t+1} = 0$, the supply chain for the specialized input remains functional, allowing the firm to purchase the specialized input on the spot market as needed. Given its production decisions in period $t+1$, the firm generates terminal cash flows, which are distributed to shareholders at the end of that period. Figure 4 summarizes this sequence of events.

4.2 Firm choices

The firm takes the prices of inputs and output as given, with these prices normalized to one. At the beginning of period t, it is endowed with liquid assets W_t and decides on how many units of generic and specialized inputs to purchase $(Q_{g,t}, Q_{s,t})$, how much inventories to hold for each

[8] The model focuses on debt as the source of external finance, reflecting the importance of trade credit in financing input purchases and inventory buildup (e.g., Rajan and Zingales, 1995; Barrot, 2016; Yang and Birge, 2018).



+
Figure 4: Model timeline
This figure shows a timeline of the model.

$(i_{g,t}, i_{s,t})$, how much cash to save (C_t), and how much debt to raise (B_t). Given input utilization $(N_{g,t} = Q_{g,t} - i_{g,t}, N_{s,t} = Q_{s,t} - i_{s,t})$, the firm generates interim cash flows by the end of period t, subject to a cash flow shock z_t. Although the manager knows the distribution of z_t, its realization is unknown when decisions are made at the beginning of period t. The firm's revenue follows a Cobb-Douglas production function:[9]

$$F(z_t, N_{g,t}, N_{s,t}) = z_t N_{g,t}^{\theta_g} N_{s,t}^{\theta_s} \tag{2}$$

where $\theta_g + \theta_s < 1$, so that there are decreasing returns to scale in the firm's production technology.

In period $t+1$, the firm's decisions are limited to procuring inputs $(Q_{g,t+1}, Q_{s,t+1})$ and issuing debt (B_{t+1}). Because the firm ceases operations at the end of period $t+1$, it does not accumulate savings or hold inventories in that period. As previously noted, if $\phi_{s,t+1} = 1$, the supply chain for the specialized input is disrupted, preventing any spot-market purchases. Consequently, specialized input utilization is determined by period $t+1$ input purchases, subject to the disruption, and the inventories from period t net of carrying costs $\alpha \in (0, 1)$. Specifically, $N_{g,t+1} = Q_{g,t+1} + (1-\alpha)i_{g,t}$

[9] The Cobb-Douglas production function assumes that both inputs are needed for production and precludes perfect substitutability between the two types of inputs. This assumption is consistent with empirical evidence showing limited substitutability across inputs during supply chain disruptions (e.g., Boehm, Flaaen, and Pandalai-Nayar, 2019).

and $N_{s,t+1} = (1 - \phi_{s,t+1})Q_{s,t+1} + (1 - \alpha)i_{s,t}$. As before, the firm generates cash flows at the end of period $t + 1$, subject to cash flow shock z_{t+1}.

4.3 Financing frictions and supply chain fragility

The firm finances its period $t+1$ input purchases using the cash flows realized at the end of period t, any cash reserves carried over from period t, and new debt raised in period $t + 1$. Financial frictions drive a wedge in the cost of external financing and internal funds. Following Nikolov and Whited (2014), I assume the firm faces quadratic financing costs ($\frac{1}{2}\lambda_t B_t^2$) for each dollar of debt raised. These frictions can be motivated by a range of theories, such as debt overhang (Myers, 1977), moral hazard (Jensen and Meckling, 1976), and adverse selection (Myers and Majluf, 1984). Additionally, the firm is subject to a debt capacity constraint (B_t^*) as in Whited and Wu (2006). I assume that $\lambda_t \geq 0$ and that the debt capacity constraint binds in each period, preventing the firm from reaching the level of production that would be optimal in a frictionless environment.

Recent models of production network formation demonstrate that supply chain fragility can emerge as an equilibrium outcome when firms optimally choose the most productive or specialized suppliers. This selection reinforces economies of scale and relationship-specific investments, resulting in a concentrated supplier base. Alternatively, technological advancements that enable or incentivize firms to incorporate a wider variety of inputs can increase production complexity and thus fragility (Oberfield, 2018; Acemoglu and Azar, 2020; Acemoglu and Tahbaz-Salehi, 2020). These equilibrium outcomes suggest that disruptions, such as supplier failures or constraints resulting from interdependent input requirements, can significantly impact firm production. Elliott, Golub, and Leduc (2022) formalize this intuition by showing that supply chains become fragile when production is susceptible to shocks, explicitly linking fragility to the degree of input specialization and the complexity of production processes. Building on their insights, I define supply chain fragility (ρ_s) as the ex ante probability that shocks disrupt suppliers of specialized inputs, formally expressed as $\rho_s = \mathbb{E}_t\mathbb{P}(\phi_{s,t+1} = 1)$.

Disruptions where $\phi_{s,t+1} = 1$ capture situations in which a firm cannot obtain inputs from a supplier, either because the supplier is not operating (e.g., due to a natural disaster) or because the price becomes prohibitively high (e.g., following a sudden regulatory intervention). The underlying assumption is that alternative suppliers may not exist, and if they do, high switching costs prevent the firm from sourcing elsewhere. The empirical evidence in Section 3, as well as in Barrot and Sauvagnat (2016), Antràs, Fort, and Tintelnot (2017), Boehm, Flaaen, and Pandalai-Nayar (2019), and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021), motivates these frictions.

4.4 Optimal policies

In period $t+1$, the firm's objective is to maximize the present value of the expected terminal value of equity, denoted by d_{t+1}, which will be distributed to current shareholders at the end of that period:

$$V_{t+1} = \max_{\{Q_{g,t+1}, Q_{s,t+1}, B_{t+1}\}} d_{t+1} \tag{3}$$

subject to,

$$Q_{g,t+1} + (1 - \phi_{s,t+1})Q_{s,t+1} \leq W_{t+1} + B_{t+1} \tag{4}$$

$$B_{t+1} \leq B^*_{t+1} \tag{5}$$

where,

$$d_{t+1} = W_{t+1} + \mathbb{E}_{t+1}F(z_{t+1}, N_{g,t+1}, N_{s,t+1}) - Q_{g,t+1} - (1 - \phi_{s,t+1})Q_{s,t+1} - B_{t+1} - \frac{1}{2}\lambda_{t+1}B^2_{t+1} \tag{6}$$

$$W_{t+1} = F(z_t, N_{g,t}, N_{s,t}) + C_t, \tag{7}$$

$$N_{g,t+1} = Q_{g,t+1} + (1 - \alpha)i_{g,t}, \tag{8}$$

$$N_{s,t+1} = (1 - \phi_{s,t+1})Q_{s,t+1} + (1 - \alpha)i_{s,t}, \tag{9}$$

and $\phi_{s,t+1}$ equals one if the supply chain of the specialized input is disrupted and zero otherwise.

Appendix B shows that, in the absence of supply chain disruptions, the firm chooses each input quantity by equating its expected marginal product to its marginal costs. These marginal costs reflect both marginal financing costs and the shadow value of debt capacity. However, if the specialized input's supply chain is disrupted, the firm cannot purchase additional units on the spot market and must rely solely on the inventory carried over from period t, net of carrying costs. In both cases, the firm's equity value at the end of period $t+1$ depends on the resource constraints it faces at the beginning of that period.

The firm is resource-constrained if its internal liquid assets, including cash flows and reserves, do not fully cover the cost of inputs in period $t+1$. Formally, the constraint can be written as follows, where internal liquidity is defined in Equation 7:[10]

$$Q_{g,t+1} + (1-\phi_{s,t+1})Q_{s,t+1} > W_{t+1} \tag{10}$$

The firm's resource constraints in period $t+1$ depend on a threshold value, Ω, for the realized cash flow shock z_t. Specifically, the firm is resource-constrained if z_t falls below Ω; otherwise, it is not. By applying the production function in Equation 2, the definition of W_{t+1} in Equation 7, and Equation 10, I derive the threshold value of z_t and obtain the following expression:

$$\Omega = \frac{Q_{g,t+1} + (1-\phi_{s,t+1})Q_{s,t+1} - C_t}{N_{g,t}^{\theta_g} N_{s,t}^{\theta_s}} \tag{11}$$

Let $d_{t+1}^{\hat{}}$ denote the value of equity at the end of period $t+1$ when the firm is resource constrained and d_{t+1}^{*} the value of equity at the end of period $t+1$ when the firm is not resource constrained. Formally, these two outcomes can be written as follows:

$$d_{t+1}^{\hat{}} = \mathbb{E}_{t+1} F(z_{t+1}, N_{g,t+1}^{\hat{}}, N_{s,t+1}^{\hat{}}) - B_{t+1} - \frac{1}{2}\lambda_{t+1} B_{t+1}^2 \tag{12}$$

$$d_{t+1}^{*} = W_{t+1} + \mathbb{E}_{t+1} F(z_{t+1}, N_{g,t+1}^{*}, N_{s,t+1}^{*}) - Q_{g,t+1}^{*} - (1-\phi_{s,t+1})Q_{s,t+1}^{*} \tag{13}$$

Since $\lambda_t > 0$ in Equation 12 and the debt capacity constraint is binding, $d_{t+1}^{\hat{}}$ is strictly less than the unconstrained optimal equity value d_{t+1}^{*}. Consequently, the expected value of equity at the end of period $t+1$ for shareholders at the start of period t can be written as follows:

$$\mathbb{E}_t V_{t+1} = \int_{-\infty}^{\Omega} d_{t+1}^{\hat{}} g(z) dz + \int_{\Omega}^{\infty} d_{t+1}^{*} g(z) dz \tag{14}$$

where $g(z)$ represents the probability density function (PDF) of z and $\mathbb{E}_t$ is the expectation conditional on information at the beginning of period t.

[10] Input inventories are excluded from the liquidity expression W_{t+1} because these inventories are typically tailored to the firm's specific needs and thus are likely to have limited value outside the firm (Shleifer and Vishny, 1991).

Therefore, assuming there is no discounting, the firm's problem in period t can be expressed as:

$$V_t = \max_{\{Q_{g,t}, Q_{s,t}, i_{g,t}, i_{s,t}, C_t, B_t\}} W_t - Q_{g,t} - Q_{s,t} - C_t - B_t - \frac{1}{2}\lambda_t B_t^2 + \mathbb{E}_t \left[\int_{-\infty}^{\Omega} \hat{d_{t+1}} g(z)dz + \int_{\Omega}^{\infty} d_{t+1}^* g(z)dz \right] \tag{15}$$

subject to,

$$Q_{g,t} + Q_{s,t} + C_t \leq W_t + B_t \tag{16}$$

$$B_t \leq B_t^*, Q_{g,t} \geq 0, Q_{s,t} \geq 0, i_{g,t} \geq 0, i_{s,t} \geq 0, C_t \geq 0 \tag{17}$$

where,

$$N_{g,t} = Q_{g,t} - i_{g,t} \tag{18}$$

$$N_{s,t} = Q_{s,t} - i_{s,t} \tag{19}$$

In Appendix B, I derive the firm's optimal inventory and cash holding policies in period t, and show how they help mitigate the impact of potential future cash flow shocks and supply chain disruptions. First, I analyze a benchmark setting where the supply chain for the specialized input is not fragile ($\rho_s = 0$). I then extend the analysis to a scenario in which the specialized input's supply chain is ex ante fragile ($\rho_s \in (0, 1)$).

4.4.1 Benchmark

If the firm expects an adverse cash flow shock and higher financing costs in period $t + 1$, it can mitigate the impact of these shocks by transferring resources from period t to period $t+1$. The firm has two options. First, it can purchase and carry inventories in period t, incurring carrying costs but ensuring that these inputs are on hand for production in period $t+1$. Alternatively, it can save cash in period t, and use these savings to finance input purchases in period $t + 1$. Proposition 1 shows that in the absence of supply chain fragility, the firm's optimal choice is to hold cash reserves rather than maintain inventories.

Proposition 1. *Suppose that $\rho_s = 0$. Then, in period t, the firm's optimal policies for $i_{g,t}$, $i_{s,t}$,* *and C_t satisfy*:

$$i^*_{g,t} = i^*_{s,t} = 0 \tag{20}$$

$$C^*_t > 0 \tag{21}$$

Proof: *See Appendix B.*

There are two primary benefits of holding cash in the absence of supply chain fragility. First, cash alleviates resource constraints that arise when debt capacity tightens, or interim cash flows decline after an adverse shock. Second, cash holdings reduce the firm's reliance on external finance, thereby lowering external financing costs. These precautionary and transactional motives for cash holdings are well-established theoretically and empirically (e.g., Keynes, 1936; Baumol, 1952; Opler, Pinkowitz, Stulz, and Williamson, 1999; Almeida, Campello, and Weisbach, 2001).

By contrast, maintaining inventories is suboptimal in the absence of supply chain fragility because the firm can purchase inputs on demand each period, and the costs of carrying inventories exceed those of holding cash. This assumption is justified by advancements in information technology, supply chain management, and lean manufacturing that have reduced transportation costs and increased the effective cost of carrying inventories.[11] Consequently, Proposition 1 is consistent with the empirical trend of decreasing inventories and increasing cash balances among U.S. firms over the last three decades (Bates, Kahle, and Stulz, 2009; Gao, 2018).

4.4.2 Ex ante supply chain fragility

When the supply chain for the specialized input is disrupted, the firm cannot acquire that input on the spot market in period $t+1$. Therefore, financial resources may be insufficient to ensure access to the specialized input, rendering production risky. Proposition 2 examines how this ex ante supply chain fragility influences the firm's optimal choices regarding inventory and cash reserves.

Proposition 2. *Suppose that $\rho_s \in (0, 1)$. Then, in period t, the firm's optimal policies for $i_{g,t}$, $i_{s,t}$,*

[11] See Ganapati and Wong (2023) for a recent discussion of these issues.

and C_t satisfy:

$$i^*_{g,t} = 0 \tag{22}$$

$$\frac{\partial i^*_{s,t}}{\partial \rho_s} > 0 \tag{23}$$

$$\frac{\partial C^*_t}{\partial \rho_s} < 0 \tag{24}$$

Proof: *See Appendix B.*

Proposition 2 suggests that, as supply chain fragility increases, the firm increases its inventories of specialized inputs and reduces its cash reserves. This adjustment reflects a change in the relative marginal benefits of holding cash versus inventories. In particular, higher fragility reduces the marginal utility of cash because the firm cannot use it to purchase specialized inputs on the spot market during disruptions. Instead, cash helps primarily in coping with the ex post consequences of disrupted inputs rather than ensuring continuous production. By contrast, holding inventories of specialized inputs ensures the firm's operational continuity and cash flow generation in the event of disruptions, making inventories a more effective tool in dealing with fragility ex ante.

This risk management strategy involves important tradeoffs. Hedging future shocks through inventory accumulation is costly, requiring firms to forgo investment opportunities and tie up working capital. As a result, firms must balance the benefits of different precautionary measures when allocating resources. The model's predictions are particularly relevant when increased fragility in specialized supply chains prompts firms to shift their hedging strategy from cash to inventories. However, cash reserves retain value for managing broader liquidity needs, such as procuring generic inputs during cash flow shocks. Therefore, while increased fragility drives a substitution from cash to inventories, the optimal level of cash does not drop to zero.

Lastly, the model also has implications for financial leverage. A higher ρ_s increases the marginal value of specialized input inventories and, at the same time, decreases the marginal value of cash holdings (Proposition 2). Appendix B shows that the optimal level of inventories increases convexly with fragility, while the optimal level of cash falls linearly. Because the change in debt is the difference between those two adjustments (Equation 16), debt issuance increases with fragility except for low levels of ρ_s. Intuitively, inventories grow faster than the decrease in cash, so new borrowing is required to cover this net spending gap.

5 The financial flexibility-corporate resilience tradeoff

This section tests the hypotheses developed in Section 4 and explores whether and how firms trade off financial flexibility for corporate resilience ex ante when faced with supply chain fragility. It also examines how bargaining dynamics between firms and their suppliers affect these outcomes.

5.1 Mapping the theory to the empirical analysis

The key parameter capturing supply chain fragility in the model presented in Section 4 is ρ_s, which represents the ex ante probability of experiencing supply chain disruptions of specialized inputs. To connect this theoretical parameter to the empirical analysis, it is helpful to express it in terms of the characteristics of specialized inputs and the likelihood of shocks. Let D_{t+1} be an indicator for supply chain shocks, defined as:

$$D_{t+1} = \begin{cases} 1 & \text{if a supply chain shock occurs at } t\text{+}1 \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

Using the law of total probability, we can write the probability of specialized supply chain disruption, $\phi_{s,t+1}$, as:

$$\mathbb{P}(\phi_{s,t+1} = 1) = \mathbb{P}(\phi_{s,t+1} = 1 | D_{t+1} = 1)\mathbb{P}(D_{t+1} = 1) + \mathbb{P}(\phi_{s,t+1} = 1 | D_{t+1} = 0)\mathbb{P}(D_{t+1} = 0) \tag{26}$$

By definition, the second term is zero since a disruption cannot occur in the absence of a shock. Let $g(R_{s,t}) \equiv \mathbb{P}(\phi_{s,t+1} = 1 | D_{t+1} = 1)$ be the conditional probability of a specialized disruption given a shock. Then, the firm-level fragility parameter, ρ_{s_i}, is:

$$\rho_{s_i} = \mathbb{E}_t g(R_{s_i,t})\mathbb{P}(D_{t+1} = 1), \tag{27}$$

where $R_{s_i,t}$ represents characteristics of the supply chain for specialized input s of firm i at time t

that make it fragile, such as the scarcity of suppliers. The function $g(.)$ is assumed to increase in $R_{s_i,t}$. Intuitively, the more fragile a specialized input's supply chain, the higher the likelihood that the firm cannot procure it after a shock. In the empirical tests, I first assume that $\mathbb{P}(D_{t+1} = 1)$ is constant across firms, and later relax this assumption by allowing firms to update their priors about supply chain fragility from realized shocks.

5.2 Supply chain fragility, corporate policies, and resilience

5.3 Ex ante effects

When $\mathbb{E}_t\mathbb{P}(D_{t+1} = 1)$ is constant across firms, the impact of supply chain fragility on corporate policies can be estimated from variation in $g(R_{s_i,t})$. To do so, I estimate firm-quarter panel regressions of the following model:

$$Y_{i,t} = \alpha_j + \alpha_t + \beta \textit{Supplier scarcity}_{i,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{28}$$

where i indexes firms, j two-digit SIC industries, and t quarters. *Supplier scarcity* is a proxy for $R_{s_i,t}$, and is defined as the additive inverse of the import volume-weighted average number of suppliers across the HS codes in firm i's import basket during quarter $t-1$. Taking the additive inverse makes *Supplier scarcity* increase with supply chain fragility.[12] Similar to Equation 1, X is a vector of firm-level controls, including the log of assets, market-to-book ratios, R&D expenditures over sales, cash flows over assets, and capital expenditures over net property, plant, and equipment. α_j and α_t denote industry and quarter fixed effects, and standard errors are clustered at the firm and quarter levels. The *Supplier scarcity* measure is highly persistent with an autocorrelation coefficient of 0.7, which is not surprising as reliance on specialized inputs is largely a function of production technologies and supply chains that likely evolve slowly over time. I, therefore, treat *Supplier scarcity* as an *ex ante* measure of supply chain fragility and focus on cross-sectional differences across firms within industries rather than within-firm variation over time.

Table 4 presents the results. The results suggest that a higher reliance on specialized inputs is associated with higher input inventory holdings, lower cash holdings, and higher book leverage.

[12] Formally, *Supplier scarcity* $= -\sum_h w_{ih,t-1} N_{h,t-1}$, where $w_{ih,t-1}$ is the import-volume share of HS code h for firm i and $N_{h,t-1}$ is the number of distinct suppliers for that code.

Table 4: Ex ante impact of supply chain fragility on input inventories, cash, and leverage
This table reports results from panel regressions of corporate policies on supplier scarcity, a proxy for ex ante supply chain fragility. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of suppliers across the HS codes in firm i's import basket during quarter $t-1$. All specifications include industry and calendar quarter fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Input inventories/Assets	Cash/Assets	Total debt/Assets
	(1)	(2)	(3)
Supplier scarcity$_{t-1}$	0.001***	$-$0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Ln(Assets)$_{t-1}$	$-$0.014***	$-$0.007***	0.029***
	(0.002)	(0.002)	(0.003)
M/B $_{t-1}$	0.001	0.001***	0.001
	(0.000)	(0.000)	(0.001)
R&D/Sales$_{t-1}$	$-$0.000*	0.002*	0.001
	(0.000)	(0.001)	(0.001)
Cash flow/Assets$_{t-1}$	$-$0.030	$-$0.252*	$-$0.498***
	(0.051)	(0.127)	(0.155)
Capex/Net PP&E$_{t-1}$	$-$0.089***	0.345***	$-$0.226***
	(0.018)	(0.037)	(0.041)
Fixed effects			
Industry	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Observations	28,801	28,801	28,801
Adj. R^2	0.20	0.21	0.21

These results are consistent with the model's predictions and are highly statistically significant. The estimated coefficients imply that a one standard deviation increase in *Supplier scarcity* is associated with 9.9% higher input inventory holdings, 12.8% lower cash holdings, and 7.8% higher book leverage relative to their mean values.[13]

5.4 Robustness and additional tests

Internet Appendix B provides additional evidence and robustness checks supporting the findings in Table 4. First, Table IA.B.3 provides a more detailed examination of how ex ante supply chain fragility affects corporate leverage. The analysis shows that the increase in leverage is primarily driven by higher accounts payable, including trade credit, and a greater use of revolving credit facilities. These results are consistent with the theory, as it suggests that firms facing specialized

[13] Table IA.B.2 reports similar estimates from cross-sectional regressions in which each observation is a firm-level average over time.

supply chain disruptions rely on short-term financing to manage increased inventory holdings.

Second, I test whether excluding domestic suppliers from the BOL data biases the results in Table 4. If the supplier scarcity measure fails to capture fragility in firms' domestic supply chains, then the baseline results should be driven by firms that rely predominantly on foreign suppliers. To evaluate this, I use Compustat segment data to calculate each firm's proportion of foreign suppliers (as reported in its 10-K) and interact that share with the supplier scarcity measure. Table IA.B.4 shows that the coefficients on supplier scarcity remain virtually unchanged from Table 4, regardless of whether a firm depends more on foreign or domestic suppliers. This suggests that supplier scarcity, the proxy for supply chain fragility, captures an inherent feature of the production process that applies to both domestic and foreign sourcing of inputs.

Third, I further validate that supplier scarcity captures supply chain fragility using anecdotal evidence from firm discussions in 10-K reports and regressions using textual measures of supply chain risk. Specifically, I show that firms with high supply chain fragility, as proxied by supplier scarcity, explicitly discuss potential supply chain shortages and related production risks. In addition, Table IA.B.6 shows that the supplier scarcity measure is strongly positively correlated with textual measures of supply chain risk derived from firms' financial reports.

Finally, I test the robustness of the results to alternative measures of $R_{s_i,t}$. Table IA.B.7 shows that the impact of supply chain fragility on corporate policies persists when measuring supply chain fragility with the share of imports of intermediate goods, specialized electronics, and scarce raw materials like semiconductors and lithium. The results also hold when fragility is measured by the complexity of a firm's input bundle, a factor that recent models have also highlighted as potentially affecting firms' sensitivity to supply chain disruptions (e.g., Elliott, Golub, and Leduc, 2022).

5.5 Learning about supply chain fragility

The panel evidence in Section 5.3 shows that firms with more fragile supply chains ex ante, as proxied by a weighted-supplier measure that is highly persistent over time, tend to hold larger input inventories, keep less cash, and have higher book leverage. These patterns are highly consistent with the comparative statics of the model in Section 4, but they do not tell us whether firms actively adjust their policies because they learn about their supply chain fragility or whether unobserved factors explain both fragility and policies. For example, unobserved characteristics of production technologies and management could simultaneously affect firms' reliance on specialized inputs and their financial policies. In this section, I exploit supplier floods as a source of exogenous variation in supply chain fragility to estimate its causal impact on corporate policies.

Supply chain shocks provide exogenous variation to identify the effect of ex ante supply chain fragility on corporate policies through a learning or salience channel. Specifically, when a flood suddenly disrupts a long-standing supplier, managers receive a signal that the supply chain risk environment they face may be worse than they thought. Formally, they may revise upward both components of the fragility parameter ρ_{s_i}. First, managers may revise their posterior estimate of the general arrival of shocks, $\mathbb{E}_t\mathbb{P}(D_{t+1} = 1)$. Second, the shock may reveal information about the technology of the supply chain itself (e.g., the difficulty in replacing suppliers of specialized inputs), leading firms to reassess $R_{s_i,t}$. Experienced-based learning (Malmendier and Nagel, 2011, 2016) and salience (Bordalo, Gennaioli, and Shleifer, 2012, 2013) predict that this revision should be larger immediately after a flood and that it should decay over time. Plugging a higher ρ_{s_i} into the comparative statics of the model produces three additional testable hypotheses: (i) firms increase holdings of input inventories in the quarters following a flood; (ii) they substitute away from cash holdings and potentially increase book leverage; and (iii) the magnitude of these adjustments increases with the number and recency of past floods.

I use the empirical strategy described in Section 3.1 to test these learning-based predictions. I focus on floods affecting specialized suppliers because these shocks align more closely with the specialized supply chain disruptions captured by the firm-level fragility parameter ρ_{s_i}. These shocks represent severe, sudden events that may immediately disrupt input availability. Because of the learning mechanism, the empirical analysis focuses on long-term changes in imports, inventories, cash holdings, and book leverage over a five-year window surrounding supply chain disruptions, rather than on short-term responses.

More precisely, I estimate stacked difference-in-differences models analogous to Equation 1 using a firm–flood-quarter panel and a symmetric five-year window around each flood. The dependent variables are the log of one plus the number of shipments, and ratios of input inventories, cash, and total debt to average pre-treatment assets.[14] Within each flood event, I define treated firms

[14] I use the log of one plus the number of shipments as dependent variable because only 3.1% of the observations are zeros in the quarterly data, and I use OLS instead of PPML for consistency. Nevertheless, the results are similar when estimating the impact on shipments using a PPML specification

as those that imported from the flood-affected suppliers at any time during the five years before the flood. Control firms are those unaffected by the current flood and any prior floods. As in Section 3, I balance treated and control firms using exact matching on two-digit SIC codes and nearest-neighbor matching on pre-treatment log assets and aggregate imports. Unlike the analysis in Section 3, the pre-treatment values of the accounting ratio outcomes are not calculated as averages because they do not exhibit seasonality. I include firm×flood and calendar quarter×flood fixed effects to estimate average treatment effects across floods. Standard errors are clustered at the firm and calendar quarter levels in all specifications. Table 4 presents estimates of the long-term treatment effects of flood shocks on corporate policies.

Column (1) shows that the log of one plus the number of shipments increases by 0.368 log points for treated firms relative to control firms in the five years following a flood, which corresponds to approximately a 44% increase in shipments. Columns (2) to (4) show that, over the same window, input inventory holdings increase by 1.8 percentage points (a 23% increase relative to the pre-treatment mean), cash holdings fall by 3.1 percentage points (a 21% decrease relative to the pre-treatment mean), and book leverage increases by 6.7 percentage points (a 19% increase relative to the pre-treatment mean). The net change in financing resources is greater than the observed increase in input inventory holdings, but it is consistent with the increase in the quantity of shipments. Because the input inventories variable measures value rather than physical units, the discrepancy between the increase in shipments and the increase in inventories may be attributed to measurement error and the decreasing unit cost associated with larger order sizes.

These results are consistent with the theoretical predictions. As perceived fragility increases, inventories of specialized inputs increase because the firm cannot procure these inputs in the spot market, and maintaining inventories ensures production continuity. The firm finances this increase with a mix of cash and debt, thereby sacrificing financial flexibility to enhance corporate resilience.

Panels A to D of Figure 5 present the event study plots for shipments, input inventories, cash holdings, and book leverage, respectively. The figure shows that pre-treatment differences between treated and control firms in the value of these outcome variables tend to be close to zero and statistically insignificant. Panels A and B show that following a flood event, there is a clear, persistent increase in shipments and input inventories to pre-treatment assets in the five years after a flood. Similarly, Panels C and D show that, after the flood, treated firms gradually and

Table 5: Long-term impact of flood shocks on input inventories, cash, and leverage
This table presents results from stacked difference-in-differences regressions of corporate policies in a five-year window around flood events. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. The data form a firm–flood event–quarter panel. *Ln(1+Shipments)* is the log of one plus the number of shipments. *Input inventories/Assets* is input inventories divided by pre-treatment assets. *Cash/Assets* is cash and short-term investments divided by pre-treatment assets. *Total debt/Assets* is the sum of current and long-term liabilities divided by pre-treatment assets. *Treated* equals one for firms that imported from a flood-affected specialized supplier at any time in the five years before the flood. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. All specifications include firm×flood and calendar quarter×flood fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

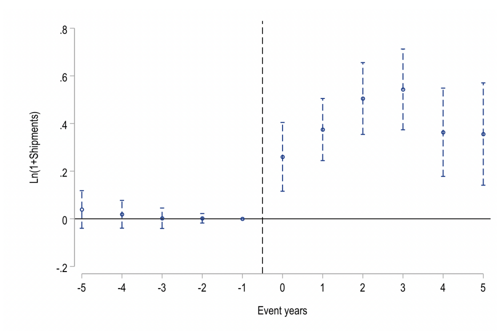
	Ln(1+Shipments)	Input inventories/Assets	Cash/Assets	Total debt/Assets
	(1)	(2)	(3)	(4)
Treated × Post	0.368^{***}	0.018^{***}	-0.031^{***}	0.067^{***}
	(0.063)	(0.004)	(0.006)	(0.020)
M/B × Post	0.023^{***}	-0.001	0.002^{*}	0.012^{***}
	(0.008)	(0.001)	(0.001)	(0.004)
Ln(Assets) × Post	-0.041^{*}	-0.012^{***}	-0.004^{**}	-0.031^{***}
	(0.020)	(0.002)	(0.002)	(0.008)
R&D/Sales × Post	0.044	0.012^{***}	0.003	0.045^{**}
	(0.033)	(0.004)	(0.006)	(0.021)
Cash flow/Assets × Post	4.542^{***}	1.159^{***}	0.636^{***}	2.245^{***}
	(1.170)	(0.161)	(0.224)	(0.513)
Capex/Net PP&E × Post	-1.828^{***}	0.029	0.294^{***}	0.019
	(0.549)	(0.040)	(0.069)	(0.162)
Fixed effects				
Firm × Flood	Yes	Yes	Yes	Yes
Calendar quarter × Flood	Yes	Yes	Yes	Yes
Observations	205,318	205,318	205,318	205,318
Adj. R^2	0.84	0.78	0.74	0.66

persistently decrease their cash holdings and significantly increase their book leverage. The fact that these effects taper off within the five-year window suggests that firms gradually reach an optimal level of inventories rather than continuously accumulating stock, which aligns with the model's prediction that firms balance the marginal benefits of additional inventory against the marginal costs of holding and financing these buffers. Together, these results strongly support a causal interpretation of the long-term changes in corporate policies following shocks to perceived supply chain fragility.

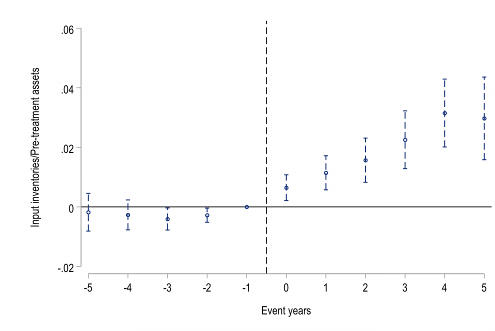
Figure 5: Corporate policies event study

This figure plots the β coefficients and 95% confidence intervals from event study regressions based on a specification analogous to Equation 1: $Y_{it} = \alpha_{ij} + \alpha_{tj} + \beta^j \sum_{s=-5}^{5} Treated_i^j \times Event\ year_s^j + \gamma X_i \times Post_t^j + \epsilon_{it}$, where i denotes firms, t quarters, and s years. $Y_{i,t}$ is *Ln(1+Shipments)*, *Input inventories/Assets*, *Cash/Assets*, or *Total debt/Assets*. $Treated_i^j$ equals one for firms where the firm imported from the flood-affected specialized supplier at any time in the five years before the flood, and $Event\ year_s^j$ is a vector of indicator variables for event years -5 through +5. $X_i \times Post_t^j$ is a vector of firm-level controls, including the log of assets, market-to-book ratios, R&D expenditures over sales, cash flows over assets, and capital expenditures over net property, plant, and equipment measured in the pre-treatment quarter, interacted with $Post_t^j$, an indicator variable that equals one during the quarters following the start of the flood. α_{ij} and α_{tj} denote firm×flood event and calendar quarter×flood event fixed effects, respectively. Standard errors are clustered at the firm and quarter levels.

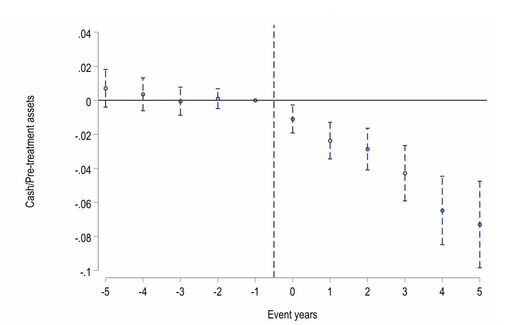
Panel A: Ln(1+Shipments)



Panel B: Input inventories/Assets



Panel C: Cash/Assets



Panel D: Total debt/Assets

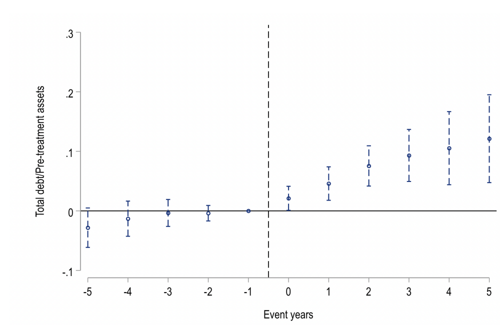


Table 6: Experience, salience, and supply chain fragility

This table presents results from stacked difference-in-differences regressions of shipments and input inventory holdings in a five-year window around flood events, including interactions with measures of flood experience and salience. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. The data form a firm–flood event–quarter panel. *Ln(1+Shipments)* is the log of one plus the number of shipments. *Input inventories/Assets* is input inventories divided by pre-treatment assets. *Treated* equals one for firms that imported from a flood-affected supplier at any time in the five years before the flood. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. *Number of prior floods* is the number of distinct specialized supplier floods the firm has experienced. *Quarters since the last flood* is the number of quarters since the firm's most recent specialized supplier flood. All specifications include firm×flood and calendar quarter×flood fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Experience learning		Salience	
	Ln(1+Shipments)	Input inventories/Assets	Ln(1+Shipments)	Input inventories/Assets
	(1)	(2)	(3)	(4)
Treated × Post	0.331***	0.015***	0.423***	0.020***
	(0.061)	(0.004)	(0.072)	(0.005)
Treated × Post × Number of prior floods	0.014**	0.001**		
	(0.006)	(0.001)		
Treated × Post × Quarters since the last flood			−0.002**	−0.001
			(0.001)	(0.000)
M/B × Post	0.023***	−0.001	0.023***	−0.001
	(0.008)	(0.001)	(0.008)	(0.001)
Ln(Assets) × Post	−0.046**	−0.012***	−0.043**	−0.012***
	(0.021)	(0.002)	(0.021)	(0.002)
R&D/Sales × Post	0.046	0.012***	0.044	0.012***
	(0.034)	(0.004)	(0.034)	(0.004)
Cash flow/Assets × Post	4.588***	1.162***	4.517***	1.157***
	(1.170)	(0.161)	(1.168)	(0.161)
Capex/Net PP&E × Post	−1.838***	0.028	−1.824***	0.030
	(0.550)	(0.040)	(0.548)	(0.040)
Fixed effects				
Firm × Flood	Yes	Yes	Yes	Yes
Calendar quarter × Flood	Yes	Yes	Yes	Yes
Observations	205,318	205,318	205,318	205,318
Adj. R^2	0.84	0.79	0.84	0.79

Under the learning and salience hypotheses, the magnitude of the change in corporate policies should increase with the number and recency of past floods. I next test for this channel by interacting $Treated \times Post$ with two proxies for experience and saliency—*Number of prior floods* and *Quarters since the last flood*—and estimate how the treatment effects on shipments and input inventory holdings vary with these measures. *Number of prior floods* counts the number of distinct specialized supplier floods the firm has experienced, a proxy for the information managers may have accumulated about supply chain fragility. *Quarters since the last flood* is the number of quarters since the firm's most recent specialized supplier flood and thus captures decay in salience.[15] If the learning and salience channels are at play, the coefficients on $Treated \times Post \times Number\ of\ prior\ floods$ should be positive, while the coefficients on $Treated \times Post \times Quarters\ since\ the\ last\ flood$ should have the opposite sign. Table 6 presents the results.

The baseline treatment effect remains positive and significant across all specifications for both shipments and input inventory holdings. Consistent with experience-based updating, the interaction terms $Treated \times Post \times Number\ of\ prior\ floods$ in columns (1) and (2) are positive and significant. Economically, each additional past flood increases the post-flood change in shipments and input inventory holdings by 1.4 percent and 0.1 percentage points (1.1% relative to the pre-treatment mean). In columns (3) and (4), the interaction term $Treated \times Post \times Quarters\ since\ the\ last\ flood$ is negative and significant for shipments and negative but insignificant for input inventories, suggesting that policy responses to supply chain shocks may decay over time. Together, these findings suggest that the impact of supply chain fragility on corporate policies, as documented in Table 5, operates through the learning and salience channels.

5.6 Bargaining and the allocation of inputs

The previous section shows that firms source more inputs and build up inventories when they perceive their supply chains to be fragile. Therefore, supplier shocks may impose physical capacity constraints on the affected suppliers not only during the disruption phase but also in the years that follow as customers build up their inventories over time. While suppliers could raise prices to clear markets during a shock, capacity constraints often bind first, making quantity rather than price

[15] Both variables are measured in the pre-treatment period and remain constant within firms. For control firms, the interaction terms are coded as zero, so the resulting coefficients capture how the treatment effect varies with prior flood experience and salience among treated firms.

the primary margin of adjustment. For example, U.S. importers received sharply fewer shipments from Japanese suppliers with almost no offsetting price increase after the 2011 Tōhoku earthquake (Boehm, Flaaen, and Pandalai-Nayar, 2019). Additionally, suppliers may prefer rationing to preserve long-term relationships with key customers rather than risk damaging these relationships through opportunistic pricing during shortages (Macchiavello and Morjaria, 2015).

Bargaining and hold-up models (Klein, Crawford, and Alchian, 1978; Grossman and Hart, 1986; Antràs and Helpman, 2004; Bimpikis, Candogan, and Ehsani, 2019) predict that scarce inputs may flow to the most valuable customers. Moreover, suppliers may engage in risk sharing with their priority customers by maintaining buffer stocks for them, providing preferential treatment when production resumes after disruptions. These bargaining considerations suggest that the cross-sectional impact of a supplier shock on corporate policies may vary depending on the relative bargaining power of customers and suppliers. This section examines these heterogeneous effects.

To examine whether firms with stronger ex ante bargaining positions adjust their policies differently after specialized supplier disruptions, I interact the $Treated \times Post$ indicator with two pre-treatment proxies for customer bargaining power: *Largest trading partner (=1)* and *Average transaction size*. *Largest trading partner (=1)* equals one if the firm accounts for the largest pre-treatment share of the specialized supplier's exports. *Average transaction size* is the firm's pre-treatment average import volume per shipment from the affected specialized supplier. Table 7 presents the results.

The baseline treatment effects for shipments and input inventory holdings remain positive and statistically significant across all specifications. Importantly, all interaction terms are negative and statistically significant. Columns (1) and (2) suggest that when the firm is the supplier's largest trading partner, the post-flood shipment increase is 0.007 log points smaller, and the input inventory buildup is 11.5 percentage points lower. Similarly, columns (3) and (4) suggest that the increase in shipments and input inventory holdings after floods is lower as firms' average transaction size with specialized suppliers affected by the floods increases.

Table 7: Customer bargaining power

This table presents results from stacked difference-in-differences regressions of of shipments and input inventory holdings in a five-year window around flood events, including interactions with measures of customer bargaining power. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. The data form a firm–flood event–quarter panel. *Ln(1+Shipments)* is the log of one plus the number of shipments. *Input inventories/Assets* is input inventories divided by pre-treatment assets. *Treated* equals one for firms that imported from a flood-affected supplier at any time in the five years before the flood. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. *Largest trading partner (=1)* equals one if the firm is the affected specialized suppliers' largest trading partner in terms of imports in the pre-treatment period. *Average transaction size* is the average import volume per shipment sourced by the firm from the affected specialized supplier in the pre-treatment period. All specifications include firm×flood and calendar quarter×flood fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Ln(1+Shipments)	Input inventories/Assets	Ln(1+Shipments)	Input inventories/Assets
	(1)	(2)	(3)	(4)
Treated × Post	0.022***	0.427***	0.020***	0.399***
	(0.004)	(0.063)	(0.004)	(0.063)
Treated × Post × Largest trading partner (=1)	−0.007**	−0.115**		
	(0.003)	(0.043)		
Treated × Post × Average transaction size			−0.002*	−0.027**
			(0.001)	(0.011)
M/B × Post	−0.001	0.024***	−0.001	0.023***
	(0.001)	(0.008)	(0.001)	(0.008)
Ln(Assets) × Post	−0.011***	−0.040*	−0.011***	−0.040*
	(0.002)	(0.020)	(0.002)	(0.020)
R&D/Sales × Post	0.012***	0.045	0.012***	0.043
	(0.004)	(0.035)	(0.004)	(0.034)
Cash flow/Assets × Post	1.158***	4.536***	1.158***	4.539***
	(0.161)	(1.176)	(0.161)	(1.170)
Capex/Net PP&E × Post	0.028	−1.846***	0.030	−1.811***
	(0.040)	(0.548)	(0.040)	(0.551)
Fixed effects				
Firm × Flood	Yes	Yes	Yes	Yes
Calendar quarter × Flood	Yes	Yes	Yes	Yes
Observations	205,318	205,318	205,318	205,318
Adj. R^2	0.79	0.84	0.79	0.84

These results suggest that customers who account for a large share of the supplier's business, or place bigger orders, have greater leverage to secure scarce inputs and don't need to stockpile as aggressively. Conversely, firms with weaker bargaining power must compensate by sourcing more shipments and holding larger precautionary inventories when perceived fragility rises. These findings are consistent with recent evidence that large firms get preferential treatment from suppliers (Franzoni, Giannetti, and Tubaldi, 2024) and with evidence of vertical risk sharing in supply chains (Macchiavello and Morjaria, 2015; Ersahin, Giannetti, and Huang, 2024a). My results add to this debate by showing that powerful customers can leverage privileged access to specialized inputs to mitigate some of the risk of fragile supply chains.

6 Real effects

Building corporate resilience to fragile supply chains is costly. First, carrying large inventories can entail substantial annual holding costs, up to 30% of inventory value, which increases operating expenses (e.g., Ramey, 1989). Second, accumulating inventories ties up financial slack that firms could otherwise use to fund investment and innovation. Moreover, tighter liquidity and higher leverage increase the shadow cost of external finance, constraining firms' investment policies (Almeida, Campello, and Weisbach, 2001). Thus, enhancing corporate resilience to supply chain disruptions may come at the expense of real activity. The next set of tests quantifies this trade-off by examining how building corporate resilience to supply chain fragility impacts costs, profitability, investment, innovation, and payout policies. To do so, I estimate the treatment effects of flood shocks on these outcomes within a five-year window around the shocks, using the same empirical strategy as in Table 5. The results are reported in Table 8.

Column (1) shows that, following a flood, treated firms experience a 0.017 percentage point increase (11% relative to the pre-treatment mean) in the cost of goods sold (COGS) over pre-treatment assets relative to control firms, which suggests that supplying firms face higher input costs when they rebuild inventories to maintain production. Consistent with these higher costs, column (2) shows a 0.021 percentage point decrease (13% relative to the pre-treatment mean) in operating margin, defined as operating income after depreciation over pre-treatment revenues.

Turning to investment decisions, column (3) indicates that treated firms decrease their capital investment, defined as capital expenditures over pre-treatment net property, plant, and equipment by 0.018 percentage points (15% relative to the pre-treatment mean), suggesting that building corporate resilience to supply chain fragility crowds out new investment. Consistent with the decrease in capital investment, column (4) shows a 0.014 percentage point decrease (33% relative to the pre-treatment mean) in innovation, defined as research and development (R&D) expenditures over pre-treatment sales.[16] Finally, column (5) reports a 0.46 percentage point decrease (44% relative to the pre-treatment mean) in repurchases over pre-treatment net income, suggesting that firms make up for lower financial flexibility by foregoing payouts to shareholders. Taken together, these results suggest that building corporate resilience to supply chain fragility raises costs, dampens growth and profitability, and constrains both investment and payout policies.

7 Conclusion

Global supply chains offer well-documented benefits, including cost efficiencies and productivity gains. However, they also expose firms to production disruptions due to policy changes, geopolitical events, natural disasters, and other shocks. This paper introduces the concept of ”supply chain fragility,” a new measure that captures firms' exposure to global supply chain shocks likely to disrupt their production, and shows that reliance on specialized inputs from global suppliers is a key determinant of this exposure.

I do so by constructing a new transaction-level dataset on the global supply chains of U.S. manufacturing firms. Using this new data and two sets of natural experiments, including supplier floods and tariff increases, I show that disruptions to specialized suppliers lead to significantly larger and more persistent adverse effects on input flows compared to disruptions affecting generic inputs. While firms can readily substitute generic suppliers through new relationship formation, they struggle to replace specialized suppliers.

To understand how firms mitigate this fragility, I then develop a model with financing frictions that incorporates the key distinction between generic and specialized inputs. The model shows that as supply chain fragility increases, firms optimally reallocate resources from cash holdings to

[16] Columns (3) and (4) control for the pre-treatment level of the outcome variables *Capex/Net PP&E* and *R&D/Sales* interacted with *Post*. These controls are not linear and account for mean reversion and differential post-shock trends. Nevertheless, the results are similar if I exclude these controls from the regressions in columns (3) and (4).

Table 8: Real effects

This table presents results from stacked difference-in-differences regressions of measures of costs, profitability, investment, innovation, and payouts in a five-year window around flood events. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. The data form a firm–flood event–quarter panel. *COGS* is the cost of goods sold divided by pre-treatment assets. *Operating margin* is operating income after depreciation divided by pre-treatment revenues. *Investment* is capital expenditures divided by pre-treatment net property, plant, and equipment. *Innovation* is research and development (R&D) expenditures divided by pre-treatment sales. *Payouts* is purchases of common and preferred stock divided by pre-treatment net income. *Treated* equals one for firms that imported from a flood-affected supplier at any time in the five years before the flood. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. All specifications include firm×flood and calendar quarter×flood fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	COGS/Assets	Operating margin	Capex/Net PP&E	R&D/Sales	Payouts
	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.017*	−0.021***	−0.018**	−0.014***	−0.460***
	(0.010)	(0.007)	(0.008)	(0.003)	(0.124)
M/B × Post	0.001*	0.004***	−0.001	0.001*	−0.039*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.022)
Ln(Assets) × Post	−0.026***	−0.005**	−0.008***	−0.002***	0.050
	(0.006)	(0.002)	(0.002)	(0.001)	(0.042)
R&D/Sales × Post	0.003	0.022**	−0.000	0.005	0.099
	(0.005)	(0.009)	(0.006)	(0.003)	(0.059)
Cash flow/Assets × Post	0.943***	0.334*	1.000***	0.304***	8.135**
	(0.263)	(0.172)	(0.244)	(0.091)	(3.650)
Capex/Net PP&E × Post	−0.063	−0.108	0.126	0.085***	0.989
	(0.095)	(0.065)	(0.126)	(0.018)	(1.055)
Fixed effects					
Firm × Flood	Yes	Yes	Yes	Yes	Yes
Calendar quarter × Flood	Yes	Yes	Yes	Yes	Yes
Observations	205,083	202,881	205,247	205,318	199,757
Adj. R^2	0.81	0.67	0.63	0.80	0.42

input inventories. This substitution reflects a change in the relative value of these instruments: cash becomes less valuable when specialized inputs lack spot markets during disruptions, while inventories ensure operational continuity. The model further predicts that firms increase leverage to make up for the financing gap between inventory investments and reduced cash holdings.

Empirically, I find strong support for these theoretical predictions using cross-sectional variation across firms within industries. In addition, using specialized supplier floods as exogenous shocks that increase perceived fragility through learning and salience channels, I also show that firms dynamically adjust their corporate policies consistent with the predictions of the model. These changes are heterogeneous across firms. Consistent with bargaining theories, firms with greater supplier bargaining power engage in less inventory accumulation after disruptions. These influential buyers can leverage privileged access to inputs during disruptions, while weaker firms must build larger buffer stocks to ensure resilience.

Building corporate resilience against supply chain fragility comes at significant cost. The financial resources allocated to inventory accumulation, combined with reduced liquidity and higher leverage, constrain firms' ability to pursue other value-creating activities. I document that firms experience higher operating costs, lower profit margins, reduced physical investment and innovation, and decreased shareholder payouts as they build resilience against specialized input disruptions.

Finally, my findings contribute to our understanding of how firms navigate the tradeoffs between operational resilience and financial flexibility in global production networks. While cash holdings have traditionally been viewed as an important tool for managing uncertainty, my research shows that when risks stem from the inability to source specialized inputs during disruptions, operational hedging through inventory accumulation becomes the optimal strategy, even at the expense of financial flexibility and real economic outcomes. These results have important implications for corporate risk management in an era of increasingly complex and fragile global supply chains.

References

Acemoglu, D., and P. D. Azar. 2020. Endogenous production networks. *Econometrica* 88:33–82.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi. 2012. The network origins of aggregate fluctuations. *Econometrica* 80:1977–2016.

Acemoglu, D., and A. Tahbaz-Salehi. 2020. Firms, failures, and fluctuations: The macroeconomics of supply chain disruptions. Working Paper.

Acharya, V., H. Almeida, Y. Amihud, and P. Liu. 2025. Corporate resiliency and the choice between financial and operational hedging. Working Paper.

Allayannis, G., J. Ihrig, and J. P. Weston. 2004. The cash flow sensitivity of cash. *Journal of Finance* 59:1777–804.

Almeida, H., M. Campello, and M. S. Weisbach. 2001. Exchange-rate hedging: Financial versus operational strategies. *American Economic Review* 91:391–395–.

Amiti, M., S. J. Redding, and D. Weinstein. 2019. The impact of the 2018 trade war on U.S prices and welfare. *Journal of Economic Perspectives* 33:187–210–.

Antràs, P. 2003. Firms, contracts, and trade structure. *The Quarterly Journal of Economics* 107:1375–418.

Antràs, P., T. C. Fort, and F. Tintelnot. 2017. The margins of global sourcing: Theory and evidence from US firms. *Journal of Political Economy* 127:509–59.

Antràs, P., and E. Helpman. 2004. Global sourcing. *Journal of Political Economy* 112:552–80.

Antràs, P., and R. W. Staiger. 2012. Offshoring and the role of trade agreements. *American Economic Review* 102:3140–3183–.

Baker, A. C., D. F. Larcker, and C. C. Y. Wang. 2022. How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144:370–95.

Barrot, J.-N. 2016. Trade credit and industry dynamics: Evidence from trucking firms. *The Journal of Finance* 71:1975–2015.

Barrot, J.-N., and J. Sauvagnat. 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics* 131:1543–92.

Bates, T. W., K. M. Kahle, and R. M. Stulz. 2009. Why do U.S. firms hold so much more cash than they used to? *The Journal of Finance* 64:1985–2021.

Baumol, W. J. 1952. The transaction demand for cash: An inventory theoric approach. *Quarterly Journal of Economics* 66:545–56.

Begenau, J., and B. Palazzo. 2021. Firm selection and corporate cash holdings. *Journal of Financial Economics* 139:697–718.

Bena, J., S. Dinc, and I. Erel. 2022. The international propagation of economic downturns through multinational companies: The real economy channel. *Journal of Financial Economics* 146:277–304.

Bimpikis, K., O. Candogan, and S. Ehsani. 2019. Supply disruptions and optimal network structures. *Management Science* 65:5504–17.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar. 2019. Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *The Review of Economics and Statistics* 101:60–75.

Bordalo, P., N. Gennaioli, and A. Shleifer. 2012. Salience theory of choice under risk. *The Quarterly Journal of Economics* 127:1243–1285–.

———. 2013. Salience and asset prices. *American Economic Review* 103:623–8.

Brunnermeier, M. K. 2024. Presidential address: Macrofinance and resilience. *The Journal of Finance* 79:3683–728.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi. 2021. Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics* 136:1255–1321–.

Carvalho, V. M., and A. Tahbaz-Salehi. 2022. Production networks: A primer. *Annual Review of Financial Economics* 11:635–63.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer. 2019. The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics* 134:1405–54.

DeAngelo, H., A. S. Gonçalves, and R. M. Stulz. 2018. Corporate deleveraging and financial flexibility. *The Review of Financial Studies* 8:3122–3174–.

Denis, D. J. 2011. Financial flexibility and corporate liquidity. *Journal of Corporate Finance* 17:667–74.

Desai, M. A., C. F. Foley, and J. Hines. 2008. Capital structure with risky foreign investment. *Journal of Financial Economics* 88:534–53.

Deshpande, M., and Y. Li. 2019. Who is screened out? Application costs and the targeting of disability programs. *American Economics Review* 11:213–48.

Dominguez, K. M. E., and L. L. Tesar. 2008. Exchange rate exposure. *Journal of International Economics* 68:188–218.

Elliott, M., B. Golub, and M. V. Leduc. 2022. Supply network formation and fragility. *American Economic Review* 112:2701–47.

Ersahin, N., M. Giannetti, and R. Huang. 2024a. Supply chain risk: Changes in supplier composition and vertical integration. *Journal of International Economics* 147:103854–.

———. 2024b. Trade credit and the stability of supply chains. *Journal of Financial Economics* 155:103830–.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal. 2020. The return to protectionism. *The Quarterly Journal of Economics* 135:1–55.

Falato, A., D. Kadyrzhanova, J. Sim, and R. Steri. 2022. Rising intangible capital, shrinking debt capacity, and the U.S. corporate saving glut. *The Journal of Finance* 77:2799–852.

Fillat, J., and S. Garetto. 2015. Risk, returns, and multinational production. *The Quarterly Journal of Economics* 130:2027–73.

Fillat, J., S. Garetto, and L. Oldenski. 2015. Diversification, cost structure, and the risk premium of multinational companies. *Journal of International Economics* 96:37–54.

Flaaen, A., F. Haberkorn, L. Lewis, A. Monken, J. Pierce, R. Rhodes, and M. Yi. 2023. Bill of lading data in international trade research with an application to the Covid-19 pandemic. *Review of International Economics* 31:1146–72.

Franzoni, F. A., M. Giannetti, and R. Tubaldi. 2024. Supply chain shortages, large firms' market power, and inflation. Working Paper.

Froot, K. A., D. S. Scharfstein, and J. C. Stein. 1993. Risk management: Coordinating corporate investment and financing policies. *The Journal of Finance* 48:1629–58.

Gabaix, X. 2011. The granular origins of aggregate fluctuations. *Econometrica* 79:733–72.

Ganapati, S., and W. F. Wong. 2023. How far goods travel: Global transport and supply chains from 1965-2020. *Journal of Economic Perspectives* 37:3–30.

Gao, X. 2018. Corporate cash hoarding: The role of just-in-time adoption. *Management Science* 64:4858–76.

Goodman-Bacon, A. 2021. Differences-in-differences with variation in treatment timing. *Journal of Econometrics* 225:254–77.

Gormley, T. A., and D. A. Matsa. 2011. Growing out of trouble? Corporate responses to liability risk. *The Review of Financial Studies* 24:2781–821.

Graham, J. R., and M. T. Leary. 2018. The evolution of corporate cash. *The Review of Financial Studies* 31:4288–344.

Grossman, S. J., and O. D. Hart. 1986. The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy* 94:691–719.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun. 2019. Firm-level political risk: Measurement and effects. *The Quaterly Journal of Economics* 134:2135–202.

Hoberg, G., and S. K. Moon. 2017. Offshore activities and financial vs operational hedging. *Journal of Financial Economics* 125:217–44.

Jang, Y. 2017. International corporate diversification and financial flexibility. *The Review of Financial Studies* 30:4133–78.

Jensen, M. C., and W. H. Meckling. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3:305–60.

Keynes, J. M. 1936. *The general theory of employment, interest and money.* New York, Harcourt Brace.

Khana, G., N. Morales, and N. Pandalai-Nayar. 2022. Supply chain resilience: Evidence from Indian firms. Working Paper.

Klein, B., R. G. Crawford, and A. A. Alchian. 1978. Vertical integration, appropriable rents, and the competitive contracting process. *Journal of Law and Economics* 21:297–326.

Kopytov, A., B. Mishra, K. Nimark, and M. Tascherau-Dumouchel. 2024. Endogenous production networks under supply chain uncertainty. *Econometrica* 92:1621–59.

Kulchania, M., and S. Thomas. 2017. Cash reserves as a hedge against supply-chain risk. *Journal of Financial and Quantitative Analysis* 52:1951–88.

Libby, R., P. A. Libby, and F. Hodge. 2019. *Financial accounting.* McGraw-Hill Education.

Lin, L., A. Mihov, and L. Sanz. 2019. Property rights institutions, foreign investment, and the valuation of multinational firms. *Journal of Financial Economics* 134:214–35.

Macchiavello, R., and A. Morjaria. 2015. The value of relationships: Evidence from a supply shock to kenyan rose exports. *American Economic Review* 126:2911–2945–.

Malmendier, U., and S. Nagel. 2011. Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics* 126:373–416.

———. 2016. Learning from inflation experiences. *Quarterly Journal of Economics* 131:53–87–.

Melitz, M. J. 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71:1695–725.

Miller, C. 2022. *Chip war: The fight for the world's most critical technology.* Simon and Schuster.

Myers, S. 1977. Determinants of corporate borrowing. *Journal of Financial Economics* 5:147–75.

Myers, S., and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 2:187–221.

Nikolov, B., and T. Whited. 2014. Agency conflicts and cash: Estimates from a dynamic model. *The Journal of Finance* 69:1883–921.

Oberfield, E. 2018. A theory of input-output architecture. *Econometrica* 86:559–89.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52:3–46.

Pankratz, N. M., and C. M. Schiller. 2025. Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies* 37:1729–77.

Rajan, R. G., and L. Zingales. 1995. What do we know about capital structure? Some evidence from international data. *The Journal of Finance* 50:1421–60.

Ramey, V. A. 1989. Inventories as factors of production and economic fluctuations. *The American Economic Review* 79:338–54.

Shleifer, A., and R. W. Vishny. 1991. Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance* 47:1343–66.

Silva, J. M. C. S., and S. Tenreyro. 2006. The log of gravity. *Review of Economics and Statistics* 88:641–58.

Smith, C. W., and R. M. Stulz. 1985. The determinants of firms' hedging policies. *Journal of Financial and Quantitative Analysis* 20:391–405.

Stulz, R. 2024. Risk, the limits of financial risk management, and corporate resilience. Working Paper.

The White House. 2021. Building resilient supply chains, revitalizing American manufacturing, and fostering broad-based growth.

Whited, T. M., and G. Wu. 2006. Financial constraints risk. *The Journal of Finance* 19:531–59.

Yang, S. A., and J. R. Birge. 2018. Trade credit, risk sharing, and inventory financing portfolios. *Management Science* 64:3667–89.

Appendix A: Variable definitions

Variable	Definition
Cash/Assets	Cash and marketable securities over assets.
Cash flow/Assets	EBITDA minus interest, taxes, and common dividends over assets.
Capex/Net PP&E	Capital expenditures over net property, plant, and equipment.
COGS	Cost of goods sold over assets.
Input inventories/Assets	Materials and supplies for use in production and in-process goods not ready for sale over assets.
M/B	One minus the sum of square import volume shares across import product HS codes in a year.
Ln(Assets)	The natural log of total assets.
Operating margin	Operating income after depreciation over revenues.
Payouts	Purchases of common and preferred stock over net income.
R&D/sales	Research and development expenditures over sales.
Supplier scarcity	The additive inverse of the import volume-weighted average number of alternative suppliers across import products in a firm's import basket.
Total debt/assets	Long-term debt plus debt in current liabilities over assets.

Appendix B: Derivations and proofs

The Lagrangian function for the firm's period $t+1$ maximization problem in Equation 3 is given by:

$$L_{t+1}(Q_{g,t+1}, Q_{s,t+1}, B_{t+1}, \mu_{t+1}, \eta_{t+1}) = d_{t+1} + \mu_{t+1}\Big[B_{t+1} + W_{t+1} - Q_{g,t+1} - (1-\phi_{s,t+1})Q_{s,t+1}\Big] + \eta_{t+1}[B^*_{t+1} - B_{t+1}] \tag{B1}$$

where,

$$d_{t+1} = W_{t+1} + \mathbb{E}_{t+1}F(z_{t+1}, N_{g,t+1}, N_{s,t+1}) - Q_{g,t+1} - (1-\phi_{s,t+1})Q_{s,t+1} - B_{t+1} - \frac{1}{2}\lambda_{t+1}B^2_{t+1}$$

and the firm's liquidity at the beginning of period $t+1$ is defined as:

$$W_{t+1} = F(z_t, N_{g,t}, N_{s,t}) + C_t$$

with the net inputs used in production given by:

$$N_{g,t+1} = Q_{g,t+1} + (1-\alpha)i_{g,t}, \quad N_{s,t+1} = (1-\phi_{s,t+1})Q_{s,t+1} + (1-\alpha)i_{s,t}$$

Here, μ_{t+1} and η_{t+1} are the Lagrange multipliers associated with the resource constraint in Equation 4 and the debt capacity constraint in Equation 5, respectively. The first-order conditions (FOCs) for the optimal decisions on $Q_{g,t+1}, Q_{s,t+1}$, and B_{t+1}, along with the conditions on the debt constraints, are derived as follows:

$$\{Q_{g,t+1}\}: \qquad \mathbb{E}_{t+1}\frac{\partial F(z_{t+1}, N_{g,t+1}, N_{s,t+1})}{\partial Q_{g,t+1}} = 1 + \mu_{t+1} \tag{B2}$$

$$\{Q_{s,t+1}\}: \qquad \mathbb{E}_{t+1}\frac{\partial F(z_{t+1}, N_{g,t+1}, N_{s,t+1})}{\partial Q_{s,t+1}} = (1-\phi_{s,t+1})(1+\mu_{t+1}) \tag{B3}$$

$$\{B_{t+1}\}: \qquad \mu_{t+1} = 1 + \lambda_{t+1}B_{t+1} + \eta_{t+1} \tag{B4}$$

$$\{\mu_{t+1}\}: \qquad B_{t+1} = Q_{g,t+1} + (1-\phi_{s,t+1})Q_{s,t+1} - W_{t+1} \tag{B5}$$

$$\{\eta_{t+1}\}: \qquad B_{t+1} = B^*_{t+1} \tag{B6}$$

In period t, the firm solves the problem in Equation 15. The Lagrangian function associated with that problem can be written as:

$$\begin{aligned}
L_t(Q_{g,t}, Q_{s,t}, i_{g,t}, i_{s,t}, C_t, B_t, \mu_t, \eta_t, \delta_{g,t}, \delta_{s,t}, \gamma_t) = W_t - Q_{g,t} - Q_{s,t} - C_t - B_t - \frac{1}{2}\lambda_t B_t^2 \\
+ \mu_t\Big[B_t + W_t - Q_{g,t} - Q_{s,t} - C_t\Big] \\
+ \eta_t(B_t^* - B_t) + \delta_{g,t} i_{g,t} \\
+ \delta_{s,t} i_{s,t} + \gamma_t C_t \\
+ \mathbb{E}_t\left[\int_{-\infty}^{\Omega} \hat{d_{t+1}} g(z)dz + \int_{\Omega}^{\infty} d_{t+1}^* g(z)dz\right]
\end{aligned} \tag{B7}$$

Here, W_t is the firm's initial endowment, and net inputs used are defined as:

$$N_{g,t} = Q_{g,t} - i_{g,t}, \quad N_{s,t} = Q_{s,t} - i_{s,t}$$

The multipliers μ_t, η_t, $\delta_{g,t}$, $\delta_{s,t}$, and γ_t correspond to the constraints in Equation 16 and Equation 17. The optimal decisions on $Q_{g,t}, Q_{s,t}, i_{g,t}, i_{s,t}, C_t, B_t,$ and the debt constraints satisfy the following FOCs:

$$\{Q_{g,t}\}: \quad \mathbb{E}_t \int_{\Omega}^{\infty} \frac{\partial F(z_t, N_{g,t}, N_{s,t})}{Q_{g,t}} g(z)dz = 1 + \mu_t \tag{B8}$$

$$\{Q_{s,t}\}: \quad \mathbb{E}_t \int_{\Omega}^{\infty} \frac{\partial F(z_t, N_{g,t}, N_{s,t})}{Q_{s,t}} g(z)dz = 1 + \mu_t \tag{B9}$$

$$\{B_t\}: \quad \mu_t = 1 + \lambda_t B_t + \eta_t \tag{B10}$$

$$\{i_{g,t}\}: \quad (1-\alpha)\mathbb{E}_t\psi = 1 + \mu_t - \delta_{g,t} \tag{B11}$$

$$\{i_{s,t}\}: \quad \left(\frac{1-\alpha}{1-\phi_{s,t+1}}\right)\mathbb{E}_t\psi = 1 + \mu_t - \delta_{s,t} \tag{B12}$$

$$\{C_t\}: \quad \mathbb{E}_t\psi = 1 + \mu_t - \gamma_t \tag{B13}$$

$$\{\mu_t\}: \quad B_t = Q_{g,t} + Q_{s,t} + C_t - W_t \tag{B14}$$

$$\{\eta_t\}: \quad B_t = B_t^* \tag{B15}$$

The term ψ is defined as:

$$\psi = \int_{-\infty}^{\Omega} (1 + \lambda_{t+1} B_{t+1}) g(z) dz + \Lambda + \int_{\Omega}^{\infty} g(z) dz, \tag{B16}$$

with

$$\Lambda = \left[F(z_{t+1}, N^*_{g,t+1}, N^*_{s,t+1}) - F(z_{t+1}, N_{g,\hat{t}+1}, N_{s,\hat{t}+1}) \right] \frac{g(\Omega)}{N^{\theta_g}_{g,t} N^{\theta_s}_{s,t}} \tag{B17}$$

The first-order conditions have a clear interpretation. When procuring inputs in period t, the firm balances the expected marginal benefit of increased cash flows, available for input purchases in period $t + 1$, against the anticipated marginal costs, which include both the cost of issuing debt in period t and the shadow value of the debt capacity constraint. Similarly, for cash and inventory holdings, the firm equates the marginal benefits to the expected marginal costs. The net marginal benefit for both inventories and cash holdings comprises the savings on financing costs when the firm faces resource constraints in period $t + 1$, the additional expected cash flow gains from alleviating these constraints, and the residual value of inventories and cash when the firm is not resource constrained.

B.1 Benchmark

Proposition 1. *Suppose that $\rho_s = 0$. Then, in period t, the firm's optimal policies for $i_{g,t}$, $i_{s,t}$, and C_t satisfy*:

$$i^*_{g,t} = i^*_{s,t} = 0$$

$$C^*_t > 0$$

Proof of Proposition 1:

First, note that when $\rho_s = 0$, the supply chain for the specialized input is not fragile, which implies that the conditions on inventories for the generic and specialized inputs are symmetric. That is,

$\delta_{g,t} = \delta_{s,t}$. Without loss of generality, consider Equation B12 and Equation B13:

$$\{i_{s,t}\}: \qquad \left(\frac{1-\alpha}{1-\phi_{s,t+1}}\right)\mathbb{E}_t\psi = 1 + \mu_t - \delta_{s,t}$$
$$\{C_t\}: \qquad \mathbb{E}_t\psi = 1 + \mu_t - \gamma_t$$

Subtracting the $\{i_{s,t}\}$ condition from the $\{C_t\}$ condition yields:

$$\delta_{s,t} = \mathbb{E}_t\alpha\psi + \gamma_t$$

Since $\mathbb{E}_t\alpha\psi + \gamma_t > 0$ (given $\alpha \in (0,1)$ and $\psi > 0$), it follows that $\delta_{s,t} > 0$. Because $\delta_{g,t} = \delta_{s,t} > 0$, the non-negativity constraints on $i_{g,t}$ and $i_{s,t}$ must bind. Therefore, the optimal inventory holdings are:

$$i^*_{g,t} = i^*_{s,t} = 0$$

The second result follows from the assumptions of the proposition. To see this, suppose by contradiction that $\gamma_t > 0$. Then, from the $\{C_t\}$ condition it would imply that the marginal benefit of holding cash is lower than one. However, this would lead to:

$$F(z_{t+1}, \hat{N_{g,t+1}}, \hat{N_{s,t+1}}) > F(z_{t+1}, N^*_{g,t+1}, N^*_{s,t+1})$$

which contradicts the optimality of the unconstrained cash decision. Therefore, it must be that $\gamma_t = 0$, ensuring that the optimal cash holding C^*_t is strictly positive.

B.2 Ex ante supply chain fragility

Proposition 2. *Suppose that $\rho_s \in (0,1)$. Then, in period t, the firm's optimal policies for $i_{g,t}$, $i_{s,t}$, and C_t satisfy*:

$$i^*_{g,t} = 0 \tag{B18}$$
$$\frac{\partial i^*_{s,t}}{\partial \rho_s} > 0 \tag{B19}$$
$$\frac{\partial C^*_t}{\partial \rho_s} < 0 \tag{B20}$$

Proof of Proposition 2:

By Proposition 1, we have $i^*_{g,t} = 0$. I now examine how an increase in ρ_s affects the marginal benefits of cash and inventory holdings. First, consider the marginal benefit of cash holdings as given in Equation B13. Using the Leibniz integral rule, the derivative of the marginal benefit of cash holdings with respect to ρ_s is:

$$\frac{\partial MB_{C_t}}{\partial \rho_s} = -\mathbb{E}_t Q_{s,t+1}\left[(1+\lambda_{t+1}B_{t+1})\frac{g(\Omega)}{N_{g,t}^{\theta_g}N_{s,t}^{\theta_s}} + \int_{-\infty}^{\Omega} \lambda_{t+1}g(z)dz\right]$$

Next, consider the first-order condition for inventory holdings of the specialized input. Again applying the Leibniz integral rule, the derivative of the marginal benefit of inventory holdings with respect to ρ_s is:

$$\frac{\partial MB_{i_{s,t}}}{\partial \rho_s} = \frac{1-\alpha}{(1-\rho_s)^2}\mathbb{E}_t\psi - \mathbb{E}_t Q_{s,t+1}\left[(1+\lambda_{t+1}B_{t+1})\frac{g(\Omega)}{N_{g,t}^{\theta_g}N_{s,t}^{\theta_s}} + \int_{-\infty}^{\Omega} \lambda_{t+1}g(z)dz\right]$$

Taking the difference between the derivatives of the marginal benefits for specialized inventories and cash, we obtain:

$$\frac{\partial MB_{i_{s,t}}}{\partial \rho_s} - \frac{\partial MB_{C_t}}{\partial \rho_s} = \frac{1-\alpha}{(1-\rho_s)^2}\mathbb{E}_t\psi$$

Since $\alpha \in (0,1)$ and $\rho_s \in (0,1)$, it follows that $\frac{1-\alpha}{(1-\rho_s)^2}\mathbb{E}_t\psi > 0$. Therefore, as ρ_s increases, the marginal benefit of holding specialized inventories increases relative to the marginal benefit of holding cash. Consequently, the optimal cash balance must decrease (i.e., $\frac{\partial C_t^*}{\partial \rho_s} < 0$) while the optimal inventory level of the specialized input increases (i.e., $\frac{\partial i^*_{s,t}}{\partial \rho_s} > 0$), *ceteris paribus*.

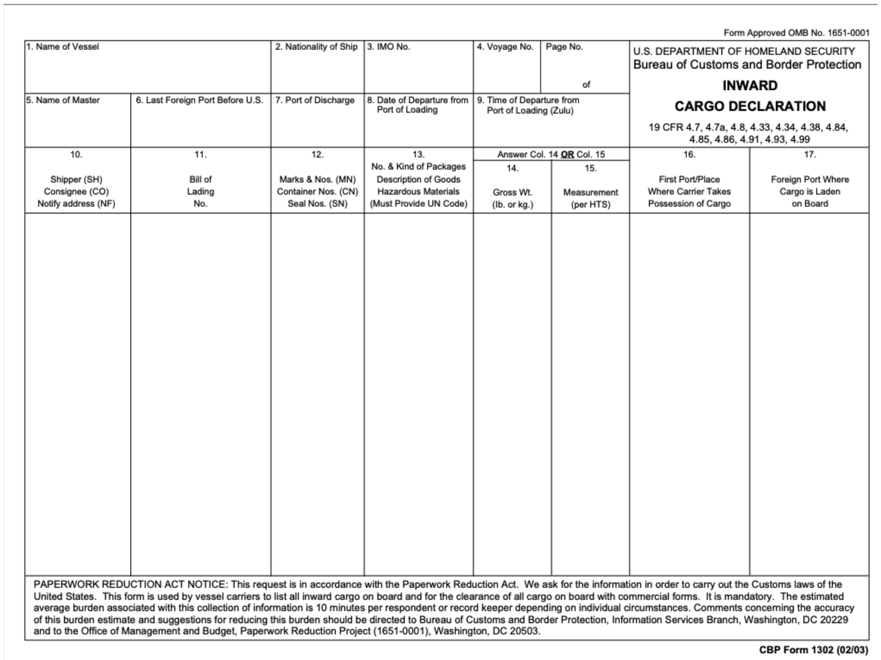
Internet Appendix for

Building Corporate Resilience to Specialized Input Disruptions

Leandro Sanz

Mendoza College of Business, University of Notre Dame

Figure IA.A.1: Bill of lading form example
This figure shows an example of a bill of lading (BoL) form.


Form Approved OMB No. 1651-0001

1. Name of Vessel		2. Nationality of Ship	3. IMO No.	4. Voyage No.	Page No. of	U.S. DEPARTMENT OF HOMELAND SECURITY Bureau of Customs and Border Protection **INWARD CARGO DECLARATION** 19 CFR 4.7, 4.7a, 4.8, 4.33, 4.34, 4.38, 4.84, 4.85, 4.86, 4.91, 4.93, 4.99	
5. Name of Master	6. Last Foreign Port Before U.S.	7. Port of Discharge	8. Date of Departure from Port of Loading	9. Time of Departure from Port of Loading (Zulu)			
10. Shipper (SH) Consignee (CO) Notify address (NF)	11. Bill of Lading No.	12. Marks & Nos. (MN) Container Nos. (CN) Seal Nos. (SN)	13. No. & Kind of Packages Description of Goods Hazardous Materials (Must Provide UN Code)	Answer Col. 14 **OR** Col. 15 — 14. Gross Wt. (lb. or kg.)	15. Measurement (per HTS)	16. First Port/Place Where Carrier Takes Possession of Cargo	17. Foreign Port Where Cargo is Laden on Board

PAPERWORK REDUCTION ACT NOTICE: This request is in accordance with the Paperwork Reduction Act. We ask for the information in order to carry out the Customs laws of the United States. This form is used by vessel carriers to list all inward cargo on board and for the clearance of all cargo on board with commercial forms. It is mandatory. The estimated average burden associated with this collection of information is 10 minutes per respondent or record keeper depending on individual circumstances. Comments concerning the accuracy of this burden estimate and suggestions for reducing this burden should be directed to Bureau of Customs and Border Protection, Information Services Branch, Washington, DC 20229 and to the Office of Management and Budget, Paperwork Reduction Project (1651-0001), Washington, DC 20503.

CBP Form 1302 (02/03)

IA.A Data

This section provides further details on the global supply chain data, presents a set of stylized facts, and reports additional analyses that validate the quality of the data and confirm that reliance on specialized inputs is a key driver of supply chain fragility.

IA.A.1 Bill of lading form example

Figure IA.A.1 shows an example of a BOL form. As illustrated, the form collects detailed information about the vessel transporting the goods and includes key logistical details such as the date of departure and arrival, the ports of lading and unlading, as well as the weight and volume occupied by the imported goods in the vessel. It also captures comprehensive data on the imported products, including product descriptions and details about both the recipient and supplier.

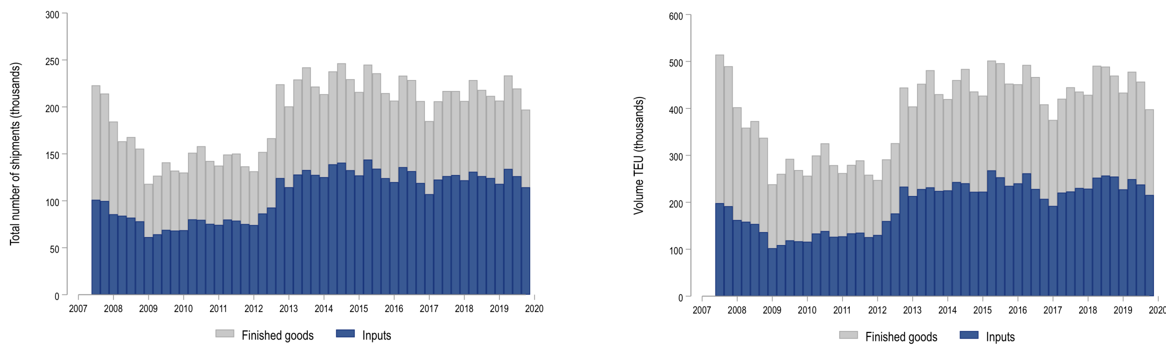
IA.A.2 Stylized facts

In this section, I present several stylized facts about the global supply chains of the sample U.S. manufacturing firms. First, I examine the evolution of aggregate imports and establish that the

Figure IA.A.2: Quarterly import activity

This figure shows the quarterly total number of shipments (Panel A) and import volume in twenty-foot equivalent units (TEUs, Panel B) sourced by sample firms from Q1 2007 to Q4 2019. In both panels, the light portion of the bars represents shipments or import volumes attributed to finished goods, while the dark potions correspond to inputs, which include raw materials and intermediate goods. Imports are classified into inputs or finished goods based on World Bank Harmonized System (HS) code definitions. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains.

Panel A: Number of shipments **Panel B:** Import volume (TEUs)



majority of these imports over the sample period consist of inputs. Next, I analyze the geographic distribution of suppliers and the structure of the network linking inputs to suppliers. Despite the global reach of these networks, imports are predominantly concentrated in a few countries, and the connections between suppliers and inputs are often sparse.

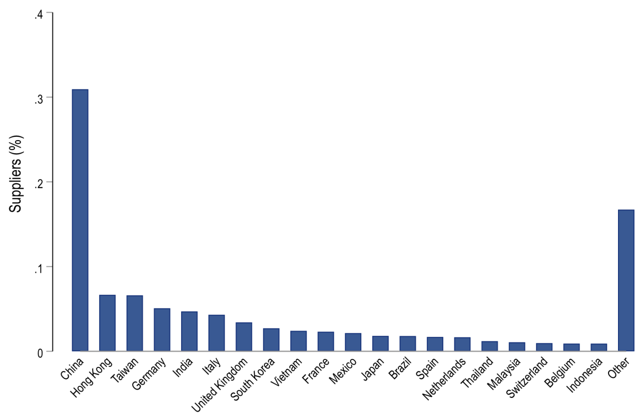
Figure IA.A.2 presents data on the total number of shipments (Panel A) and the total import volume in TEUs (Panel B) for sample manufacturing firms. Since 2007, these firms have received over 500,000 shipments via maritime transport, totaling more than 1 million TEUs. The figures peaked in 2014–2015 when firms received nearly 1 million shipments and 1.8 million TEUs. However, during economic downturns, such as the global financial crisis, both the total number of shipments and import volume experienced a marked decline.

The figure also breaks down the total imports of U.S. manufacturing firms into raw materials and intermediate goods (collectively referred to as inputs), and finished goods. Over the sample period, inputs represent 55% of imports, while finished products account for the remaining 45%. These statistics are consistent with the growing importance of specialized intermediate inputs relative to final goods in international trade (Antràs and Staiger, 2012).

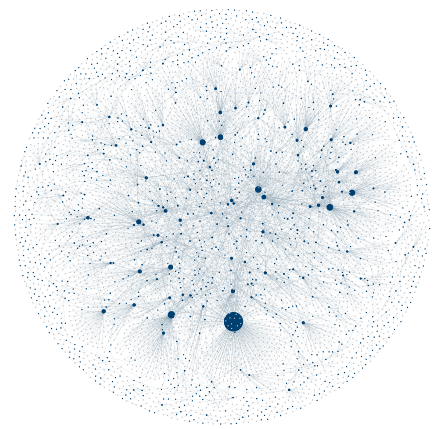
Panel A of Figure IA.A.3 illustrates the country distribution of foreign suppliers for sample U.S. manufacturing firms in 2019, highlighting the extensive reach of these global supply chains,

Figure IA.A.3: Country distribution and network structure of global suppliers
Panel A of this figure displays the country distribution of foreign suppliers for the sample firms in 2019. Panel B illustrates the network structure of inputs and their suppliers over the period Q1 2007 to Q4 2019. In Panel B, blue nodes represent unique inputs classified by their Harmonized System (HS) codes, while gray dots denote individual suppliers. The edges between nodes indicate sourcing relationships, illustrating which suppliers provide specific inputs to a node. Larger blue nodes correspond to more generic inputs. The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains.

Panel A: Country distribution of suppliers



Panel B: Input-supplier network



which include over 25,000 foreign suppliers across 156 countries. However, the distribution is highly uneven. For example, in 2019, 31% of the foreign suppliers in the BOL data were located in China. Panel B of Figure IA.A.3 further shows that the network structure of inputs and suppliers is highly heterogeneous. While there is a large number of suppliers for some inputs, others are provided by only a few, as indicated by the isolated node pairs on the periphery of the graph.

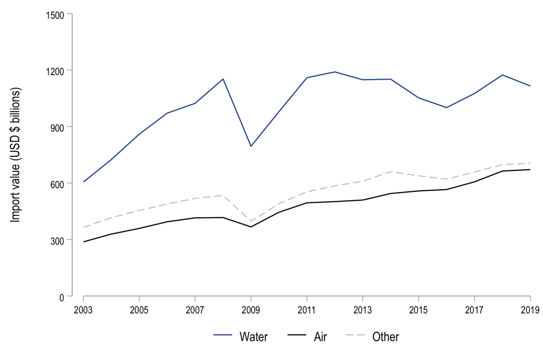
IA.A.3 Maritime imports vs. other modes of transportation

As discussed in Section 2.2, one limitation of the BOL data is that it only records imports obtained via maritime shipments. In this section, I examine whether the global supply chains constructed from the BOL data are representative of firms' overall global supply chains. To do so, I compare the evolution of aggregate U.S. import value and weight by mode of transportation, including maritime shipments, air shipments, and other modes, using U.S. Census Bureau data.

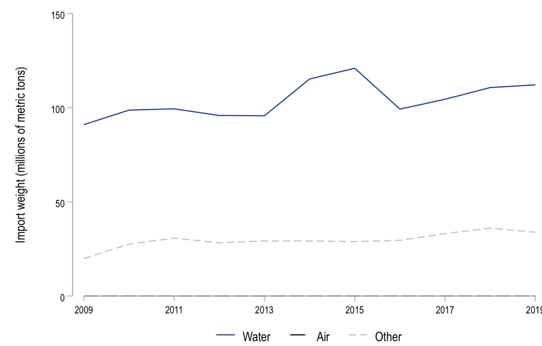
Panel A of Figure IA.A.4 shows that maritime shipments' import value has consistently outpaced that of other transportation modes from 2003 to 2019. This trend is even more pronounced for import weight. As shown in Panel B, maritime imports far exceed those of any other transportation

Figure IA.A.4: Evolution of imports by mode of transportation
This figure shows the time series of aggregate U.S. imports by mode of transportation (Water, Air, and Other). The "Other" category includes pipeline, truck, and rail imports. In Panel A, imports are measured in dollar values for the period 2003 to 2019. In Panel B, they are measured in weight for the period 2009 to 2019. These data are from the U.S. Census Bureau.

Panel A: Import value



Panel B: Import weight



mode from 2009 to 2019.[17]

Next, I examine how the aggregate value of maritime and air imports differs across HS product codes, focusing on the top ten HS codes ranked by the dollar value of aggregate imports for each transportation mode. Panels A and B of Figure IA.A.5 show the annual percentage of imports attributed to these HS codes from 2009 to 2019 for maritime and air imports, respectively.[18]

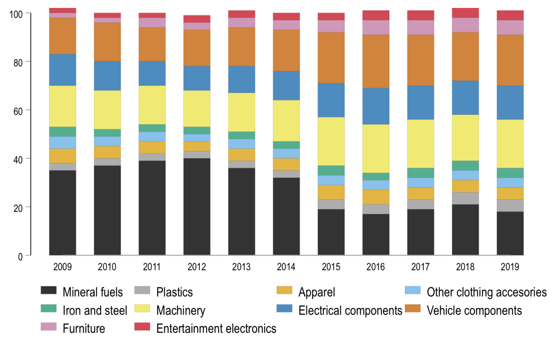
The composition of the top ten HS codes for maritime and air imports highlights notable differences in the mode of transportation used across product categories. For example, mineral fuels—which, on average, account for 26% of maritime imports among the top ten HS codes—are absent from the top ten HS codes for air imports. Conversely, pharmaceuticals consistently represent a significant share of air imports each year, yet they are missing from the top ten HS codes for maritime imports.

The fact that pharmaceutical imports are not well represented in maritime shipments is not a significant issue for this analysis, as pharmaceutical manufacturing firms make up only about 7% of the sample. Moreover, specialized components heavily used by other manufacturing firms, such as electronic equipment and machinery, are well represented in both air and maritime imports, collectively accounting for approximately one-third of the imports among the top ten HS codes

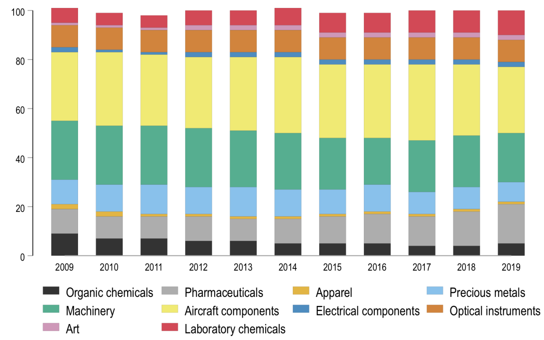
[17] The time series for import weight by mode of transportation began in 2009. The average weight of air imports during this period is only 0.007 million metric tons.
[18] The decomposition of imports across HS product categories is available starting in 2009.

Figure IA.A.5: Product composition of maritime and air imports
This figure shows the composition of maritime (Panel A) and air (Panel B) imports across the ten most common Harmonized System (HS) codes ranked by the dollar value of imports from 2009 to 2019. These data are from the U.S. Census Bureau.

Panel A: Maritime imports



Panel B: Air imports



for each mode. These statistics suggest that analyses based on maritime import data effectively capture the supply chain characteristics relevant to the majority of manufacturing firms in the sample.

IA.B Additional results and robustness tests

This section presents additional results and robustness tests that are described and referenced in the manuscript.

IA.B.1 Specialized supply chains and corporate resilience, alternative specifications

This section replicates the baseline results in column (1) of Panels A and B of Table 2 under several alternative specifications. First, I re-estimate the model using the PPML estimator, with import volume as the dependent variable. Second, I estimate the treatment effects *Ln(1+Shipments)* and *Ln(1+Volume)* with ordinary least squares (OLS). Finally, still with OLS, I use the number of shipments and import volume as a percent of pre-treatment assets as dependent variables. Panel A of Table IA.B.1 presents the results for floods, and Panel B for tariffs.

For Panel A, the coefficient in column (1) implies a 36% decrease in import volume after a supplier flood, almost identical to the estimate in Panel A of Table 2. Columns (4) and (5) show comparable effects when the dependent variables are the number of shipments or import volume as a percent of pre-treatment assets. These estimates suggest a 38% decrease in the number of shipments and a 34% decline in import volume relative to their mean values. By contrast, columns (2) and (3), which use *Ln(1+Shipments)* and *Ln(1+Volume)* as dependent variables, yield smaller effects of 19% and 22%, respectively. This attenuation is expected because the log transformation compresses the scale of large import flows. In contrast, the PPML specification keeps the data in levels, thereby preserving the full magnitude of changes, especially for large pre-treatment flows that drop to zero. The results in Panel B of Table IA.B.1 are similar to those in Panel A. The specifications in columns (1), (4), and (5) suggest treatment effects comparable to column (1) of Table 2, Panel B, whereas columns (2) and (3) produce smaller estimates.

Table IA.B.1: Specialized inputs and supply chain fragility, alternative specifications

This table presents results from stacked difference-in-differences regressions of the number of shipments over two distinct event windows: a four-week window around flood events (Panel A) and a six-month window around tariff waves (Panel B). The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q4 2007 to Q4 2019. In Panel A, the data form a firm–supplier–flood event–week panel, while in Panel B, the data form a firm–supplier–tariff wave–month panel. Column (1) reports PPML estimates with import volume as the dependent variable. Columns (2) and (3) show OLS results using *Ln(1+Shipments)* and *Ln(1+Volume)* as dependent variables, respectively. Columns (4) and (5) use the number of shipments and import volume, each expressed as a percentage of pre-treatment assets, as dependent variables. *Treated* equals one for firm–supplier pairs where the firm imported from a flood- (tariff-) affected supplier at any time in the five years before the event. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. All specifications include firm×supplier×event and calendar time×event fixed effects. Standard errors clustered at the firm and calendar time levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel A: Floods					
	Volume	Ln(1+Shipments)	Ln(1+Volume)	Shipments/Assets	Volume/Assets
	(1)	(2)	(3)	(4)	(5)
Treated × Post	−0.440***	−0.189***	−0.221***	−0.045***	−0.100***
	(0.038)	(0.011)	(0.014)	(0.009)	(0.026)
Ln(Assets) × Post	0.020	0.002	−0.006	0.055***	0.077***
	(0.016)	(0.004)	(0.005)	(0.014)	(0.018)
M/B × Post	−0.000	−0.000	−0.001	−0.000	−0.002
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
R&D/Sales × Post	−0.018	−0.004***	0.002	−0.171***	−0.004
	(0.200)	(0.001)	(0.002)	(0.003)	(0.006)
Cash flow/Assets × Post	0.650	−0.150	−0.100	1.247**	2.157*
	(0.931)	(0.242)	(0.305)	(0.583)	(1.177)
Capex/Net PP&E × Post	1.041***	0.143*	0.115	0.194	0.310
	(0.248)	(0.074)	(0.119)	(0.136)	(0.248)
Fixed effects					
Firm × Supplier × Flood	Yes	Yes	Yes	Yes	Yes
Firm × Flood	No	No	No	No	No
Calendar week × Flood	No	No	No	No	No
Observations	563,796	563,796	563,796	563,796	563,796
Pseudo R^2	0.71	0.41	0.50	0.43	0.42

Table IA.B.1: Specialized inputs and supply chain fragility, alternative specifications, continued

This table presents results from stacked difference-in-differences regressions of the number of shipments over two distinct event windows: a four-week window around flood events (Panel A) and a six-month window around tariff waves (Panel B). The sample consists of 923 publicly listed U.S. manufacturing firms with global supply chains from Q4 2007 to Q4 2019. In Panel A, the data form a firm–supplier–flood event–week panel, while in Panel B, the data form a firm–supplier–tariff wave–month panel. Column (1) reports PPML estimates with import volume as the dependent variable. Columns (2) and (3) show OLS results using *Ln(1+Shipments)* and *Ln(1+Volume)* as dependent variables, respectively. Columns (4) and (5) use the number of shipments and import volume, each expressed as a percentage of pre-treatment assets, as dependent variables. *Treated* equals one for firm–supplier pairs where the firm imported from a flood- (tariff-) affected supplier at any time in the five years before the event. Treated and control firms are balanced by exact matching on two-digit SIC codes and nearest matching on the pre-treatment log of assets and aggregate imports. All specifications include firm×supplier×event and calendar time×event fixed effects. Standard errors clustered at the firm and calendar time levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel B: Tariffs	Volume	Ln(1+Shipments)	Ln(1+Volume)	Shipments/Assets	Volume/Assets
	(1)	(2)	(3)	(4)	(5)
Treated × Post	−0.582***	−0.276***	−0.288***	−0.154***	−0.465**
	(0.136)	(0.028)	(0.030)	(0.042)	(0.167)
Ln(Assets) × Post	0.034	−0.006	−0.008	−0.037	−0.177**
	(0.039)	(0.009)	(0.009)	(0.027)	(0.077)
M/B × Post	0.014	0.005	0.005	0.002	−0.007
	(0.014)	(0.004)	(0.004)	(0.004)	(0.016)
R&D/Sales × Post	−0.191	0.002	0.011	−0.133***	−0.256
	(0.177)	(0.013)	(0.014)	(0.047)	(0.187)
Cash flow/Assets × Post	1.143	0.737	0.637	−2.096	−5.866
	(4.727)	(0.694)	(0.775)	(2.421)	(8.296)
Capex/Net PP&E × Post	3.547***	0.103	0.030	0.792	5.413*
	(0.727)	(0.242)	(0.265)	(0.555)	(3.068)
Fixed effects					
Firm × Supplier × Tariff wave	Yes	Yes	Yes	Yes	Yes
Firm × Tariff wave	No	No	No	No	No
Calendar month × Tariff wave	No	No	No	No	No
Observations	480,993	482,857	482,857	482,857	482,857
Pseudo R^2	0.79	0.61	0.64	0.48	0.42

Table IA.B.2: Supply chain fragility and corporate policies, cross-sectional results
This table reports results from regressions of corporate policies on supplier scarcity, a proxy for ex ante supply chain fragility. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of suppliers across the HS codes in firm i's import basket during quarter $t-1$. Robust standard errors are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Input inventories/Assets	Cash/Assets	Total debt/Assets
	(1)	(2)	(3)
Supplier scarcity	0.001^{**}	-0.004^{***}	0.003^{***}
	(0.000)	(0.001)	(0.001)
Ln(Assets)	-0.013^{***}	-0.001	0.024^{***}
	(0.002)	(0.003)	(0.004)
M/B	-0.002^{***}	0.006^{***}	0.005
	(0.001)	(0.002)	(0.003)
R&D/Sales	0.000	-0.001	0.001
	(0.000)	(0.001)	(0.001)
Cash flow/Assets	-0.005	-0.802^{***}	-0.475^{*}
	(0.079)	(0.180)	(0.247)
Capex/Net PP&E	-0.157^{***}	0.615^{***}	-0.466^{***}
	(0.032)	(0.073)	(0.077)
Fixed effects			
Industry	No	No	Yes
Quarter	No	No	Yes
Observations	909	909	909
Adj. R^2	0.11	0.33	0.16

IA.B.2 Cross-sectional results

As explained in Section 5.3, firm-level supplier scarcity is highly persistent over time, suggesting that firm-level variation in the reliance on specialized inputs is predominantly cross-sectional. Therefore, in this section, I examine the relationship between corporate policies and supply chain fragility using purely cross-sectional variation. To do this, I estimate cross-sectional regressions with one observation per firm, where variables are averaged over the sample period. Standard errors in these regressions are robust to heteroskedasticity. The cross-sectional results in Table IA.B.2 are consistent with those in Table 4, though the point estimates are slightly larger in magnitude.

IA.B.3 Debt decomposition

As shown in Section 5, ex ante supply chain fragility significantly increases firm book leverage. To explore this further, I decompose the effect of fragility on leverage by debt type using annual

Table IA.B.3: Debt decomposition

This table reports results from panel regressions of different debt instrument ratios on supplier scarcity, a proxy for ex ante supply chain fragility. The sample is a firm-year panel of 923 publicly listed U.S. manufacturing firms with global supply chains from 2007 to 2019. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of suppliers across the HS codes in firm i's import basket during year $t-1$. All specifications include industry and calendar year fixed effects. Standard errors clustered at the firm and calendar year levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Accounts payable	Revolving credit	Term loans	Commercial paper	Bonds
	(1)	(2)	(3)	(4)	(5)
Supplier scarcity$_{t-1}$	1.297**	0.020***	0.010	−0.000	−0.055
	(0.428)	(0.005)	(0.011)	(0.001)	(0.060)
M/B$_{t-1}$	−0.021	0.000	−0.000	0.000**	0.001
	(0.026)	(0.000)	(0.000)	(0.000)	(0.001)
Ln(Assets)$_{t-1}$	−0.232*	−0.009***	−0.004**	0.002***	0.033**
	(0.106)	(0.001)	(0.001)	(0.000)	(0.011)
R&D/Sales$_{t-1}$	−0.336***	−0.001	−0.003*	0.000**	−0.001
	(0.088)	(0.001)	(0.001)	(0.000)	(0.006)
Cash flow/Assets$_{t-1}$	−4.584***	0.038**	−0.040	0.001	−0.255**
	(0.889)	(0.015)	(0.028)	(0.002)	(0.105)
Capex/Net PP&E$_{t-1}$	0.195	−0.046***	−0.043*	0.000	−0.144
	(0.861)	(0.013)	(0.022)	(0.002)	(0.124)
Fixed effects					
Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	7,776	7,776	7,776	7,776	7,776
Adj. R^2	0.22	0.06	0.04	0.08	0.01

data.[19] Specifically, I examine accounts payable (including trade credit), revolving credit facilities, term loans, commercial paper, and bonds. The findings, reported in Table IA.B.3, suggest that the overall increase in book leverage stems mainly from higher use of accounts payable (trade credit) and revolving credit facilities.

[19] I use annual rather than quarterly data because debt-type data is better populated at the yearly frequency.

IA.B.4 Controlling for the importance of domestic suppliers

A limitation of the BOL supply chains data is that it tracks only international shipments. Therefore, a natural concern is that a proxy of supply chain fragility derived from this data might be specific to foreign inputs rather than the whole firm. If that were true, the proxy should matter only for firms with predominantly foreign supply chains and should be largely irrelevant for firms with a high proportion of domestic suppliers.

To test this prediction, I use Compustat segments data based on financial disclosures to calculate the proportion of foreign suppliers for each firm. These data list both domestic and foreign suppliers as long as they are material enough to be named in firm's disclosures. I compute *Foreign suppliers (%)*, the fraction of disclosed suppliers that are foreign, and interact it with the supplier scarcity measure. If foreign suppliers drive the impact of supplier scarcity on corporate policies, then this should be reflected in the interaction term. Table IA.B.4 presents the results.

The estimated coefficients on the standalone *Foreign suppliers (%)* variable or the interaction terms are not statistically significant in any of the columns. Additionally, the estimated coefficients on the supplier scarcity variable are nearly identical to those reported in Table 4. These results suggest that proxies of supply chain fragility derived from the BOL data are representative of firm-level risks associated with specialized inputs, regardless of whether these inputs are sourced domestically or internationally.

IA.B.5 Reliance on specialized inputs and supply chain risk

The empirical framework assumes that a greater reliance on specialized inputs, or disruptions to suppliers of such inputs, serves as a good proxy for supply chain fragility. To validate this assumption, I examine the correlation between specialized input dependence and perceived supply chain risk. I begin by presenting ten illustrative cases of firms with the highest fragility scores, based on the supplier scarcity measure. Table IA.B.5 lists these companies, along with their industries and brief product descriptions. The firm with the highest fragility score based on the supplier scarcity measure is One Stop Systems, Inc. (OSS). According to its website, OSS "designs and manufactures innovative edge computing modules and systems for AI transportable applications, including ruggedized servers, compute accelerators, expansion systems, flash storage arrays, and

Table IA.B.4: Controlling for the importance of domestic suppliers

This table reports results from panel regressions of corporate policies on supplier scarcity, a proxy for ex ante supply chain fragility, and interactions with the proportion of foreign suppliers. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of suppliers across the HS codes in firm i's import basket during quarter $t-1$. *Foreign suppliers (%)* is the proportion of a firm's foreign suppliers. All specifications include industry and calendar quarter fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Input inventories/Assets	Cash/Assets	Total debt/Assets
	(1)	(2)	(3)
Supplier scarcity$_{t-1}$	0.001***	−0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Foreign suppliers (%)$_{t-1}$	0.001	0.027	−0.060
	(0.009)	(0.019)	(0.045)
Supplier scarcity$_{t-1}$ × Foreign suppliers (%)$_{t-1}$	0.002	−0.002	−0.001
	(0.001)	(0.003)	(0.003)
Ln(Assets)$_{t-1}$	−0.014***	−0.007***	0.030***
	(0.002)	(0.002)	(0.003)
M/B$_{t-1}$	0.000	0.001***	0.001
	(0.000)	(0.000)	(0.001)
R&D/Sales$_{t-1}$	−0.000*	0.002*	0.001
	(0.000)	(0.001)	(0.001)
Cash flow/Assets$_{t-1}$	−0.030	−0.249*	−0.504***
	(0.051)	(0.127)	(0.155)
Capex/Net PP&E$_{t-1}$	−0.089***	0.343***	−0.223***
	(0.018)	(0.037)	(0.041)
Fixed effects			
Industry	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Observations	28,801	28,801	28,801
Adj. R^2	0.20	0.21	0.21

Ion Accelerator™ SAN, NAS, and data recording software. These products are used for AI data-set capture, training, and large-scale inference in defense, oil and gas, mining, autonomous vehicles, and rugged entertainment applications." This profile implies a heavy dependence on highly specialized components. Indeed, OSS explicitly acknowledges supply chain risks in the "Nature of Operations" section of its recent 10-Q reports, warning that such risks could constrain its ability to attract customers and innovate.

The remaining firms likewise produce highly specialized products that require specialized inputs. For example, this group includes companies that manufacture sophisticated communication devices and healthcare firms that produce diagnostic instruments and surgical devices. Notably, Yeti Holdings explicitly acknowledges in its financial disclosures the procurement challenges it faces for

Table IA.B.5: Top ten firms by supplier scarcity

This table lists the ten firms with the most fragile supply chains, as measured by supplier scarcity. To rank the firms, I computed the within-firm average of the supplier scarcity measure from 2007 to 2019 and then ranked them based on this average. Additionally, the table provides details on each firm's industry and a concise description of their primary products. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019.

Rank	Firm name	Industry	Product summary
(1)	(2)	(3)	(4)
1	One Stop Systems	Electronic computers	Various AI transportable systems
2	Sientra	Surgical appliances	Plastic surgery materials and technologies
3	A10 Networks	Computer communications equipment	Application delivery controllers
4	Zynex	Electromedical apparatus	Electrotherapy devices
5	Chembio Diagnostics	Diagnostic substances	Diagnostics technologies
6	Ubiquiti	Communications equipment	Specialized communications equipment
7	Lantheus Holdings	Diagnostic substances	Diagnostics medical imaging products
8	Merit Medical Systems	Surgical appliances	Cardiology diagnostics
9	Yeti Holdings	Sporting and athletic goods	Outdoor products
10	Orasure Technologies	Diagnostic substances	Diagnostic testing kits

critical raw materials, such as polyethylene, from its suppliers.

Next, I examine the correlation between perceived supply chain risk and supplier scarcity more broadly by using a textual analysis approach similar to Hassan, Hollander, van Lent, and Tahoun (2019). Specifically, I identify passages in firms' annual 10-K reports that discuss supply chain risk by distinguishing language patterns indicative of such risk from ordinary financial report text. To do so, I construct a "non-risk" corpus from the tenth edition of Libby, Libby, and Hodge (2019), which represents typical financial disclosure language. As the "risk" corpus, I use the The White House (2021) report on building resilient supply chains, which provides targeted terminology related to supply chain risks.

I then convert these texts into bigrams and calculate a score by measuring the differences in bigrams in a ten-word radius of keywords such as "risk" and "uncertainty" in the 10-Ks and the reference texts. Finally, this score is normalized by the total bigram count in the 10-K documents. By focusing on bigrams that appear near "risk" or "uncertainty" and comparing their frequency to the reference texts, this method quantifies how extensively and in what contexts firms discuss supply chain risk in their 10-K reports. Additionally, I compute the cosine similarity between the White House report's bigram frequency vector and the 10-K's bigram vector. This measure captures the overall textual similarity of the 10-Ks to supply chain risk language, regardless of

Table IA.B.6: Supplier scarcity and textual measures of supply chain risk

This table reports results from regressions of textual measures of supply chain risk on supplier scarcity, a proxy for ex ante supply chain fragility. The sample is a firm-year panel of 923 publicly listed U.S. manufacturing firms with global supply chains from 2007 to 2019. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of suppliers across the HS codes in firm i's import basket during year $t-1$. The textual measure of supply chain risk is constructed using a bigram approach in column (1) and a cosine similarity approach in column (2). For the bigram approach, I calculate the proportion of bigrams in firms' 10-K reports associated with discussions of supply chains around synonyms of risk and uncertainty similar to Hassan et al. (2019). For the cosine similarity approach, I calculate the cosine similarity of the word-count vectors of firms' 10-K reports and The White House (2021) report on building resilient supply chains. t-statistics based on standard errors clustered at the firm level are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

	Bigrams	Cosine similarity
	(1)	(2)
Supplier scarcity	0.061**	1.847***
	(0.029)	(0.230)
Fixed effects		
Industry	Yes	Yes
Year	Yes	Yes
Observations	10,005	10,005
Adj. R^2	0.31	0.70

explicit mentions of "risk" or "uncertainty."

Finally, I regress the supplier scarcity measure on the textual measures of supply chain risk derived from the bigram and cosine similarity approaches as dependent variables. The findings, presented in Table IA.B.6, show a robust positive correlation between the supplier scarcity measure and supply chain risk discussions in financial disclosures. This strong correlation further supports the validity of the supplier scarcity measure as a credible proxy for supply chain fragility.

IA.B.6 Alternative measures of supply chain fragility

In this section, I consider alternative measures of supply chain fragility. The first measure is the proportion of imports classified as intermediate inputs. A higher proportion suggests a greater reliance on specialized inputs, which may indicate increased fragility in the supply chain. The second measure focuses on the proportion of imports consisting of specialized electronics and scarce raw materials. These inputs are often critical to production and are typically concentrated among a small number of suppliers, as highlighted by Miller (2022). Their share in total imports can, therefore, serve as an indicator of supply chain fragility.

I categorize imports into intermediate inputs, specialized electronics, and scarce raw materials using the Harmonized System (HS) codes. For intermediate inputs, I use World Bank classifications. For specialized electronic components, I use classifications by the U.S. Census Bureau, supplemented by manual classifications informed by The White House (2021)'s report on building resilient supply chains.[20]

The third measure builds on Elliott, Golub, and Leduc (2022), who argue that the technological complexity of a firm's input bundle determines how severely a supply chain disruption to any single specialized supplier affects production. In their framework, complexity rises with the number of distinct inputs firms need to produce and with the degree of complementarity among them. I define input complexity as one minus the sum of the squares of import shares across import product HS codes in a year. This measure increases with the the number of distinct inputs the firm relies on.

Table Table IA.B.7 reports regressions analogous to Table 4 but replacing supplier scarcity with the alternative measures of supply chain fragility defined above. Panel A focuses on input inventories, Panel B on cash holdings, and Panel C on book leverage. Across the three panels, the results confirm that irrespective of the empirical measure of supply chain fragility used, the key conclusions from Table 4 remain consistent. Specifically, supply chain fragility is associated with higher input inventory holdings, lower cash holdings, and higher book leverage.

[20] The U.S. Census Bureau tracks imports of specialized electronics across ten categories: Biotechnology, Life Science, Opto-Electronics, Information & Communications, Electronics, Flexible Manufacturing, Advanced Materials, Aerospace, Weapons, and Nuclear Technology.

Table IA.B.7: Alternative measures of supply chain fragility

This table reports results from panel regressions of corporate policies on alternative measures of ex ante supply chain fragility. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. *Intermediate inputs import share* is the share of imports comprised of intermediate inputs. *Specialized inputs import share* is the share of imports comprised of specialized electronics and scarce raw materials. *Input complexity* is defined as one minus the sum of square import shares across import product HS codes. Panel A presents results for input inventories, Panel B for cash holdings, and Panel C for book leverage. All specifications include industry and calendar quarter fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel A: Input inventories			
	Input inventories/Assets		
	(1)	(2)	(3)
Intermediate inputs import share$_{t-1}$	0.020***		
	(0.007)		
Specialized inputs import share$_{t-1}$		0.094**	
		(0.046)	
Input complexity$_{t-1}$			0.013**
			(0.006)
Ln(Assets)$_{t-1}$	−0.013***	−0.013***	−0.013***
	(0.001)	(0.001)	(0.001)
M/B$_{t-1}$	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
R&D/Sales$_{t-1}$	−0.001**	−0.001**	−0.001**
	(0.000)	(0.000)	(0.000)
Cash flow/Assets$_{t-1}$	−0.010	−0.006	−0.013
	(0.049)	(0.049)	(0.049)
Capex/Net PP&E$_{t-1}$	−0.090***	−0.097***	−0.091***
	(0.017)	(0.017)	(0.017)
Fixed effects			
Industry	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Observations	33,656	33,914	33,794
Adj. R^2	0.20	0.20	0.20

Table IA.B.7: Alternative measures of supply chain fragility, continued

This table reports results from panel regressions of corporate policies on alternative measures of ex ante supply chain fragility. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. *Intermediate inputs import share* is the share of imports comprised of intermediate inputs. *Specialized inputs import share* is the share of imports comprised of specialized electronics and scarce raw materials. *Input complexity* is defined as one minus the sum of square import shares across import product HS codes. Panel A presents results for input inventories, Panel B for cash holdings, and Panel C for book leverage. All specifications include industry and calendar quarter fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel B: Cash holdings			
	Cash/Assets		
	(1)	(2)	(3)
Intermediate inputs import share$_{t-1}$	-0.035^{***}		
	(0.009)		
Specialized inputs import share$_{t-1}$		-0.070^{***}	
		(0.018)	
Input complexity$_{t-1}$			-0.074^{***}
			(0.011)
Ln(Assets)$_{t-1}$	-0.012^{***}	-0.012^{***}	-0.008^{***}
	(0.002)	(0.002)	(0.002)
M/B$_{t-1}$	0.002^{***}	0.002^{***}	0.002^{***}
	(0.000)	(0.000)	(0.000)
R&D/Sales$_{t-1}$	0.002^{**}	0.002^{**}	0.002^{**}
	(0.001)	(0.001)	(0.001)
Cash flow/Assets$_{t-1}$	-0.361^{***}	-0.351^{***}	-0.340^{**}
	(0.128)	(0.128)	(0.131)
Capex/Net PP&E$_{t-1}$	0.351^{***}	0.335^{***}	0.336^{***}
	(0.037)	(0.037)	(0.036)
Fixed effects			
Industry	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Observations	33,656	33,914	33,794
Adj. R^2	0.20	0.20	0.21

Table IA.B.7: Alternative measures of supply chain fragility, continued

This table reports results from panel regressions of corporate policies on alternative measures of ex ante supply chain fragility. The sample is a firm-quarter panel of 923 publicly listed U.S. manufacturing firms with global supply chains from Q1 2007 to Q4 2019. *Intermediate inputs import share* is the share of imports comprised of intermediate inputs. *Specialized inputs import share* is the share of imports comprised of specialized electronics and scarce raw materials. *Input complexity* is defined as one minus the sum of square import shares across import product HS codes. Panel A presents results for input inventories, Panel B for cash holdings, and Panel C for book leverage. All specifications include industry and calendar quarter fixed effects. Standard errors clustered at the firm and calendar quarter levels are reported in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance levels are denoted by ***, **, *, respectively. Appendix A presents variable definitions.

Panel C: Book leverage			
	Total debt/Assets		
	(1)	(2)	(3)
Intermediate inputs import share$_{t-1}$	0.021		
	(0.016)		
Specialized inputs import share$_{t-1}$		0.052***	
		(0.019)	
Input complexity$_{t-1}$			0.039***
			(0.014)
Ln(Assets)$_{t-1}$	0.032***	0.032***	0.030***
	(0.003)	(0.003)	(0.003)
M/B$_{t-1}$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
R&D/Sales$_{t-1}$	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Cash flow/Assets$_{t-1}$	−0.458***	−0.469***	−0.477***
	(0.127)	(0.129)	(0.129)
Capex/Net PP&E$_{t-1}$	−0.229***	−0.219***	−0.226***
	(0.038)	(0.038)	(0.038)
Fixed effects			
Industry	Yes	Yes	Yes
Quarter	Yes	Yes	Yes
Observations	33,656	33,914	33,794
Adj. R^2	0.22	0.23	0.23