Supply Network Fragility, Inventory Investment, and Corporate Liquidity

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Abstract

This study uses a novel dataset of over 11,000 foreign suppliers to U.S. manufacturers to investigate the impact of supply network fragility on corporate policies. The scarcity of suppliers offering specialized inputs emerges as a key driver of fragility. Both theoretical and empirical evidence indicate that firms with fragile supply networks maintain more input inventories, less cash, and higher leverage. Moreover, plausibly exogenous variation in fragility from technology adoption and disruptions supports a causal interpretation of the results. My findings indicate that because specialized inputs lack a spot market post-disruptions, firms with fragile supply networks favor operational over financial hedging.

JEL Codes: G31, G32, F23, L23

Keywords: Production networks; global supply chains; corporate liquidity; inventories

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1 Introduction

Global supply networks have become a cornerstone of the world economy. Their cost efficiency and productivity enhancements are well documented (Kugler and Verhoogen, 2009; Halpern, Koren, and Szeidl, 2015). However, they also expose firms to various potential disruptions, from geopolitical incidents to natural disasters. The literature has primarily focused on how firms respond to these shocks ex-post (e.g., Barrot and Sauvagnat, 2016; Boehm, Flaaen, and Pandalai-Nayar, 2019) and their contribution to aggregate economic fluctuations, such as macroeconomic volatility (e.g., Gabaix, 2011; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012). However, the ex-ante impact of these shocks on corporate policies is not fully understood. This knowledge gap is critical. Supply network fragility—specifically, the likelihood that supply network disruptions hamper firm production—can be a substantial ex-ante risk for companies and affect their decisions.

I argue that reliance on specialized inputs and the scarcity of their suppliers play pivotal roles in shaping the impact of supply network fragility on corporate policies. To substantiate this claim, I incorporate supply network fragility into a standard investment model with financing frictions and derive implications of fragility for corporate policies. I then test the model's predictions by analyzing novel data on the global supply networks of a sample of publicly listed U.S. manufacturing firms. The analysis uncovers that firms with fragile supply networks stockpile more input inventories, maintain lower cash reserves, and incur higher debt. Therefore, the paper highlights how firms trade off operational hedging by bolstering their production resilience with higher input inventories and financial flexibility when mitigating the ex-ante risk of fragile supply networks.

These findings align with recent models of supply network formation, which suggest that the degree to which supply network disruptions impact firm production is contingent upon the nature of the inputs sourced and the structure of the network (Oberfield, 2018; Acemoglu and Azar, 2020; Acemoglu and Tahbaz-Salehi, 2020; Elliott, Golub, and Leduc, 2022). Thus, supply network fragility can be viewed as an interaction between the ex-ante risk of supply network disruptions and pre-existing characteristics of inputs and suppliers that exacerbate the impact of such disruptions on firms. The recent challenges faced by the U.S. automotive industry serve as an example of this dynamic. Specifically, the shortage of computer chips and other specialized automotive components contributed to an approximate 10% reduction in vehicle production in 2022.[1]

In the model, a firm relies on generic and specialized inputs to generate revenue, subject to cash flow shocks. A critical distinction between these inputs is that while generic inputs are consistently accessible in the spot market, specialized inputs lack a spot market following disruptions. The financing of these input purchases depends on interim cash flows, cash reserves, or external finance. The model emphasizes debt over equity for external financing due to its key role in funding input purchases and inventory accumulation (Rajan and Zingales, 1995; Barrot, 2016; Yang and Birge, 2018). The firm faces financing frictions when issuing debt, including financing costs and debt capacity constraints. Crucially, the supply network for the specialized input may be disrupted with some probability, preventing access to the spot market for such input and forcing reliance on inventories for production.

The model predicts that firms with fragile supply networks ex-ante optimally hold more specialized input inventories and less cash than those with robust supply networks. Intuitively, this result arises in the model because maintaining specialized input inventories is an effective operational hedge against disruptions. For instance, by utilizing its inventory stock, the firm can continue its production and cash flow generation during disruptions. By contrast, while the traditional precautionary and transaction motives for cash holdings (Keynes, 1936; Baumol, 1952) remain, cash holdings are less effective in preemptively addressing disruptions. This is because, following disruptions, no spot markets are available for acquiring specialized inputs. Thus, cash holdings are only helpful in dealing with the ex-post consequences of such disruptions.

Moreover, the marginal benefit of input inventory holdings over cash increases non-linearly in the model with the likelihood or severity of disruptions. Thus, in cases where it is optimal for the firm to increase inventories to a larger degree than it decreases cash holdings, the firm will resort to external finance to make up for the difference. Since debt is the primary mode of external finance for input purchases and inventory buildup (Rajan and Zingales, 1995; Barrot, 2016; Yang and Birge, 2018), the model predicts that financial leverage will increase when supply network fragility is particularly severe.

[1] See "Why the Automotive Chip Crisis Isn't Over (Yet)," by Kristin Dziczek, October 2022, *Chicago Fed Letter*.

To empirically test the model's predictions, I use a novel and detailed dataset on the global supply networks of publicly listed U.S. manufacturing firms from 2007 to 2021. The data are derived from administrative bill of lading (BoL) documents maintained by the U.S. Department of Homeland Security, Bureau of Customs and Border Protection (CBP). These records provide comprehensive daily information on the maritime import activities of U.S. firms.

The granularity and breadth of the BoL data provide a distinct advantage over prior studies that use financial reports to deduce customer-supplier linkages. 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 buyers (Carvalho and Tahbaz-Salehi, 2022). Importantly, I validate the quality of the BoL data with other data sources and show that the maritime supply networks characterized by the BoL data are likely an accurate representation of these firms' broader global supply networks.

Using the BoL data, I construct an empirical measure of ex-ante supply network fragility that aligns with the concept of fragility in my theoretical model and the recent supply network formation literature.[2] This metric, which I term "supplier scarcity," gauges the availability of alternative suppliers for a firm's inputs. The underlying premise is that inputs with fewer alternative suppliers are highly specialized, making firm output more susceptible to supply disruptions. Hence, I infer that firms facing greater supplier scarcity have more fragile supply networks.

I find strong support for the model's predictions using this empirical measure of supply network fragility.[3] Specifically, by leveraging cross-sectional variation in supply network fragility among firms within and across sectors, I find that firms with fragile networks consistently have larger inventories of inputs, lower cash-to-asset ratios, and higher book leverage compared to otherwise similar firms. The magnitudes of these effects are economically large. For example, a one standard deviation increase in supplier scarcity is associated with a 6.6% increase in the ratio of input inventories, such as raw materials and work-in-process goods, to assets relative to its mean value. Similarly, the same increase in supplier scarcity corresponds to 13.3% lower cash-to-asset ratios and

[2] For instance, the distribution of indegrees in production networks—the count of suppliers per product—is pivotal in depicting the structure of U.S. input-output tables in Acemoglu and Azar (2020). Likewise, the number of available suppliers for an input is a critical aspect of what Elliott, Golub, and Leduc (2022) describe as supply network functionality—a factor influencing a firm's vulnerability to idiosyncratic supplier shocks.

[3] The results are robust to alternative measures of supply network fragility that account for firms' dependence on specialized inputs. These alternative measures are strongly correlated with supplier scarcity.

3.4% higher book leverage, both relative to their respective mean values.[4]

There are important endogeneity concerns with the analyses presented thus far. First, there is a possibility that firms with fragile supply networks are inherently innovative, and such innovative firms are known to maintain higher cash reserves and have lower debt capacity (Bates, Kahle, and Stulz, 2009; Falato, Kadyrzhanova, Sim, and Steri, 2022). If so, the coefficient estimates would be biased toward zero. Second, the empirical measure of supply network fragility may suffer from classical measurement error, which could attenuate the estimated relationship between fragility and corporate policies. Third, recent studies on endogenous production network formation have emphasized multi-sourcing as a strategy to mitigate supply network fragility (Elliott, Golub, and Leduc, 2022; Kopytov, Mishra, Nimark, and Tascherau-Dumouchel, 2022). Although this strategy might be challenging for firms that rely on specialized inputs from a limited pool of suppliers, it raises potential reverse causality concerns, which would bias coefficient estimates away from zero. Specifically, financially constrained firms, possibly indicated by low cash-to-assets ratios and high leverage, might struggle to diversify their suppliers, leading to increased fragility.

To address these concerns, I first implement an Instrumental Variables (IV) strategy that exploits plausibly exogenous variation in contemporaneous supply network fragility resulting from firms' adoption of technologies in the 1980s and 1990s that increased their reliance on specialized inputs. To construct this instrument, I first identify a set of terms related to emerging technologies and advanced materials as discussed in Industry Week articles from 1986 to 1995.[5] Initially, I identify a set of words in Industry Week articles that discuss emerging technologies. Next, I refine this list by manually identifying a random set of technologies and materials likely conducive to reliance on specialized inputs. Lastly, I use the curated list to train a word embedding algorithm that searches for additional relevant terms by analyzing the contextual interrelations of terms in the texts. The final list includes terms such as "semiconductor," "laser," and "silicon."

[4] The findings indicate a larger decrease in cash relative to the increase in inventories and a corresponding rise in leverage, diverging from the theoretical predictions. This discrepancy may arise because cross-sectional variation may not fully capture corporate policy dynamics. Nonetheless, dynamic analyses around supply disruptions reveal leverage adjustments aligning with the model's predictions, with changes in leverage mirroring the inventory-cash differential.

[5] Industry Week is a reputable information resource for management professionals in the manufacturing sector, providing insights on topics such as best practices, strategic planning, operations management, and, notably, technological developments within the industry.

As a final step, I calculate the frequency of mentions of the identified terms in firms' financial disclosures from 1986 to 1995 using novel textual data predating the widespread accessibility of these disclosures ushered by the Security and Exchange Commission's (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system in 1996. I use the frequency of terms related to technology adoption from 1986 to 1995 as an instrument for supplier scarcity from 2007 to 2021. The analysis establishes a robust correlation between the historical measure of technology adoption and supplier scarcity during the sample period.

The strength of the instrument is evidenced by the first-stage F-statistics ranging from 143.07 to 154.45, figures that not only surpass the conventional benchmarks for weak instruments as suggested by Stock and Yogo (2005) but also exceed the more stringent threshold of 104.7, which is recommended for a reliable five percent t-test in the recent IV inference literature (Lee, McCrary, Moreira, and Porter, 2022). This high level of relevance of the instrument mitigates weak instrument concerns that could otherwise undermine the validity of the IV estimates. Additionally, the second-stage estimates are consistent with the initial results, and by isolating plausibly exogenous variation in supply network fragility, they lend a causal interpretation to my findings.

The validity of the IV strategy hinges on the exclusion restriction, which asserts that the instrument should influence corporate policies solely through its effect on supplier scarcity. While one cannot directly test this assumption, I offer two pieces of evidence supporting it. Firstly, the historical measurement of technology adoption inherently limits the direct contemporaneous effects of technology adoption on corporate policies. Over long horizons, the influence of technology adoption on production input requirements is likely to be more persistent than on immediate corporate policy decisions. For instance, Apple's 2007 adoption of touch-screen technology for the iPhone led to a sustained reliance on Indium Tin Oxide, a specialized substance that makes the glass touch-sensitive. Yet, the immediate impact of Apple's adoption of that technology on outcomes such as investment, R&D spending, and operating flexibility is unlikely to persist today. Consistent with this view, I demonstrate that the technology adoptions of the late 1980s and early 1990s do not significantly affect investment, R&D spending, or operating flexibility in the 2010s.

Secondly, I investigate if the instrument influences supplier scarcity through the proposed mechanism: a sustained increase in reliance on specialized inputs, which, due to their concentrated global supply, leads to fragile supply networks (Miller, 2022). The evidence indicates that technology adoption during the 1980s and 1990s had a lasting effect on specialized inputs reliance, as evidenced by a strong positive correlation between the instrument and imports of specialized inputs in the 2010s.

In addition to the IV strategy, I directly examine the multi-sourcing strategy to mitigate supply network fragility in a setting where these pre-established multi-sourcing relationships could be highly valuable. The idea behind this strategy is that firms could establish multi-sourcing agreements in advance to circumvent input shortages during supply disruptions. To examine this, I consider the 2018-2019 tariffs on certain imports from China as a persistent shock that substantially increased the costs of procuring inputs from Chinese suppliers. These tariffs provide an ideal setting to assess the multi-sourcing hypothesis, as switching suppliers can entail significant fixed costs even when pre-existing contracts are in place (Antràs, 2003). Consequently, firms might be reluctant to bear these costs if they anticipate transient supply network disruptions.

The tariffs were implemented in four phases between July 2018 and September 2019, significantly increasing the cost of sourcing over 10,000 product categories from China. The median tariff hike across these phases was 25%, a substantial rise considering that many affected products were not subject to tariffs before 2018. The empirical tests aim to discern whether firms switch to alternative suppliers at the intensive margin in response to a lasting disruption and the extent to which financial resources enable such shifts.

To analyze the tariffs' impact on input sourcing, I employ a stacked difference-in-differences methodology (Gormley and Matsa, 2011; Cengiz, Dube, Lindner, and Zipperer, 2019; Deshpande and Li, 2019; Baker, Larcker, and Wang, 2022). This method estimates treatment effects within each tariff implementation wave and aggregates them across the waves. This approach mitigates biases inherent to the canonical difference-in-differences framework in staggered settings, which arise from comparing newly treated firms to those with unchanged treatment status (Goodman-Bacon, 2021). Firms' treatment status is based on whether they imported any tariff-affected product categories from China the year before tariff enactment. My findings reveal no significant shift away from Chinese suppliers up to a year after the tariffs, regardless of their financial strength before the tariffs.[6] These results suggest that despite the potential advantages of multi-sourcing, firms do not readily transition away from suppliers facing disruptions. Moreover, they suggest that multi-sourcing may be less practical than recent theories propose. These findings are consistent with other studies documenting low elasticities of substitution across suppliers following disruptions when such suppliers offer differentiated goods (Barrot and Sauvagnat, 2016; Khana, Morales, and Pandalai-Nayar, 2022).

The final identification strategy leverages plausible exogenous variation in the second component of supply network fragility, the expected likelihood of disruptions. This approach addresses another significant concern: the possibility that specialized inputs necessitate firm-specific investments, thereby constraining firms' ability to switch suppliers, even when alternative suppliers are available. If this is the case, the analysis might understate the true extent of supply network fragility, or more critically, the observed effects might reflect bargaining dynamics rather than indicate the risk management of supply network fragility. The "hold-up" problem, where firms might adjust policies to avoid being exploited by dominant suppliers (Klein, Crawford, and Alchian, 1978; Hart and Moore, 1988, 1990), exemplifies this concern.

To disentangle the effects of supplier market power from supply network fragility, I use floods at supplier locations as shocks to managers' subjective probability assessments of future disruptions and, in turn, fragility. Importantly, unlike variation in supply network fragility from technology adoption, these shocks are orthogonal to supply network characteristics like input specificity and supplier market power. Moreover, the focus is not on the accuracy of these subjective probabilities or potential behavioral biases but on ensuring that policy adjustments are not merely reactions to the floods. Therefore, I analyze the evolution of corporate policies within five years surrounding these short-lived floods.

I draw on data from over 2,000 flood incidents recorded by the University of Colorado's Dartmouth Flood Observatory for these tests. I categorize a supplier as exposed to a flood event if the distance between the supplier and the affected region falls within the area (in square miles) impacted by the flood. I first demonstrate that, in the cross-section, firms exposed to a flood event

[6] To avoid the confounding impacts of the COVID-19 pandemic, observations after December 2019 are not included in these tests.

through their suppliers tend to increase input inventories and reduce cash holdings, with these effects becoming stronger in the five years after a flood event. These effects are particularly pronounced when the impacted suppliers are difficult to replace. In that case, leverage also increases following floods at supplier locations.

Next, I investigate within-firm changes in imports and corporate policies in a staggered difference-in-differences setting. As before, I use a stacked regression approach that estimates treatment effects within each firm-flood event. In addition, since any particular disaster may only impact a small subset of firms, I ensure that treated and control firms are balanced by requiring they are in the same two-digit SIC code and similar in observables, such as size and their import activity in the year before treatment. This methodology reveals that imports from suppliers that experienced a natural disaster increase significantly in the year following the floods. Additionally, affected firms' input inventories and leverage increase proportionally while their cash holdings decrease marginally. These within-firm findings align with the cross-sectional results, reinforcing the conclusion that supply network fragility has a tangible effect on corporate policies, even in scenarios where bargaining dynamics are unlikely to be influential. In addition, they support the theoretical predictions regarding financial leverage, which posit that financial leverage is likely to increase proportionally to specialized input purchases as the likelihood of supply network disruptions increases.

This paper contributes to several literature streams. First, it complements the growing body of research on firms' strategic responses to vulnerabilities in production networks. While prior research has predominantly been theoretical, focusing on how firms might adjust their production networks to mitigate supply risks both at the intensive (Oberfield, 2018; Bimpikis, Candogan, and Ehsani, 2019; Acemoglu and Azar, 2020) and extensive margins (Acemoglu and Tahbaz-Salehi, 2020; Elliott, Golub, and Leduc, 2022; Kopytov et al., 2022), it often presumes that firms can diversify their supply bases by forging new supplier contracts. A few concurrent empirical studies have examined adjustments in supply network composition at the extensive margin in response to supply chain risk (Ersahin, Giannetti, and Huang, 2022; Khana, Morales, and Pandalai-Nayar, 2022; Pankratz and Schiller, 2023). In contrast, my paper utilizes unique, detailed data on global supply networks to investigate how firms strategically adapt their corporate policies in response to ex-ante supply network fragility. My research reveals that while strategic reconfiguration of supply networks at the extensive margin is a common theoretical solution, it may be practically difficult when alternative suppliers for specialized inputs are scarce. This insight underscores the complexities firms face when attempting to mitigate supply network fragility and contributes a nuanced understanding of the interplay between supply chain risk and corporate decision-making.

Second, my research contributes to the literature on corporate hedging. Firms can hedge to reduce their risk exposures, circumvent the costs associated with financial distress, or prevent missing out on valuable investment opportunities (Smith and Stulz, 1985; Froot, Scharfstein, and Stein, 1993). When markets are complete, and trading in underlying assets is liquid, firms may opt for hedging through derivative contracts and insurance. Alternatively, firms often rely on their financial and operational policies as hedging mechanisms in the absence of such conditions. Several studies emphasize that cash holdings, or more generally maintaining financial flexibility, are effective hedges against adverse cash flow shocks and shocks to the cost of external finance (e.g., Gamba and Triantis, 2014). My research adds to a growing literature emphasizing that cash holdings may not be an effective hedge for certain risks, such as risks in the sourcing of inputs, and that firms may substitute operational for financial hedging (e.g., Hoberg and Moon, 2017; Bianco and Gamba, 2018; Acharya, Almeida, Amihud, and Liu, 2022). Particularly, my findings reveal that in scenarios where specialized inputs lack accessible spot markets post-disruptions, firms favor operational hedging over financial hedging—they opt for higher input inventory holdings at the expense of lower cash holdings and higher leverage.

Third, my research also adds to the literature on the trends in corporate cash holdings, leverage, and inventory management, as well as the interactions of these policies (e.g., Bates, Kahle, and Stulz, 2009; Denis, 2011; DeAngelo, Gonçalves, and Stulz, 2018; Graham and Leary, 2018; Begenau and Palazzo, 2021; Falato et al., 2022). Bates, Kahle, and Stulz (2009) argue that changes in firm characteristics have been a driving factor behind the substantial increase in cash ratios since the early 2000s. They note that companies with leaner inventory levels and more intangible asset investments maintain higher cash balances. This trend may be partly attributed to technological improvements in inventory management systems, such as just-in-time processes, which could allow firms to hold less inventory and more cash (Gao, 2018). However, my study reveals that this substitution effect may reverse under conditions of supply network fragility. In such scenarios, firms prioritize operational continuity over financial flexibility, opting to bolster their inventories of inputs to ensure production resilience. This adjustment suggests a nuanced relationship between inventory and cash holdings, where the nature of inventories—whether it is finished goods ready for sale or inputs required for production—plays a critical role in influencing firms' liquidity management strategies. When supply networks are fragile, input inventories become a strategic asset, potentially leading to a reevaluation of the conventional wisdom regarding the substitutability of cash and inventories in a firm's working capital structure.

Finally, my research offers insights into the literature on the advantages and risks associated with multinational operations. Multinational corporations (MNCs) often enjoy a broader spectrum of financing opportunities due to their presence in various local capital markets (Jang, 2017). However, they also face unique risks due to their international activities (Antràs, Fort, and Tintelnot, 2017). The sunk costs tied to foreign investments can limit diversification benefits and increase the correlation of cash flows with the broader economy (Melitz, 2003; Fillat and Garetto, 2015; Fillat, Garetto, and Oldenski, 2015). Additionally, MNCs are susceptible to political uncertainties (Desai, Foley, and Hines, 2008), potential expropriation (Lin, Mihov, and Sanz, 2019), and currency fluctuations (Dominguez and Tesar, 2008) in their operational jurisdictions. By focusing on the risks arising from sourcing inputs through fragile supply networks, my study adds a new dimension to the ongoing debate. It highlights that beyond the general risks of multinational operations, global sourcing of specialized inputs can pose significant challenges for firms.

2 Model

In this section, I present a simple, two-period model of a firm that faces adverse cash flows and supply network shocks. I use the model to demonstrate how the firm mitigates the impact of these shocks ex-ante and to derive testable hypotheses about optimal policies on inventory holdings, cash balances, and leverage.

2.1 Model setup and timing

Following Elliott, Golub, and Leduc (2022), I model supply network fragility as an inherent characteristic of the production process and the inputs it requires. Specifically, I consider a firm that employs two distinct types of inputs for production: a generic input, denoted by g, and a specialized input, denoted by s. The generic input is readily available on the spot market, guaranteeing the firm's continuous access to suppliers. In contrast, the specialized input is not procurable on the spot market, either because of the geographic distribution of scarce materials or because they require relationship-specific investments.

The firm exists for two periods. In the initial period, t, the firm makes decisions regarding production inputs, inventory levels, cash reserves, and debt financing.[7] In the subsequent period, $t+1$, it determines its production inputs and debt financing needs. Given the production decisions made in period t, the firm generates interim cash flows at the end of that period. These interim cash flows, along with the cash saved from period t, can finance the procurement of production inputs in period $t+1$.

The firm's ability to source the specialized input in period $t+1$ is contingent on the parameter $\phi_{s,t+1}$. If $\phi_{s,t+1} = 1$, the supply network for the specialized input is disrupted before period $t+1$, compelling the firm to rely solely on its inventory of specialized inputs accumulated from period t. If $\phi_{s,t+1} = 0$, the supply network for the specialized input is operational, and the firm can purchase the input on the spot market as needed.

Given production decisions in period $t+1$, the firm generates terminal cash flows, which are then distributed to shareholders at the end of that period. Figure 1 summarizes the model's timeline.

2.2 Details on firm choices and notation

The firm takes the prices of inputs and output as given, with these prices normalized to one. At the outset of period t, the firm is endowed with liquid assets W_t and decides on the quantities of generic and specialized inputs to purchase $(P_{g,t}, P_{s,t})$, the inventory levels to maintain for each $(i_{g,t}, i_{s,t})$,

[7] The model focuses on debt rather than equity as the source of external finance. This choice reflects the fact that trade credit (a form of debt) is a critical source of external finance for corporations, particularly for input purchases and inventory build-up (e.g., Rajan and Zingales, 1995; Barrot, 2016; Yang and Birge, 2018).

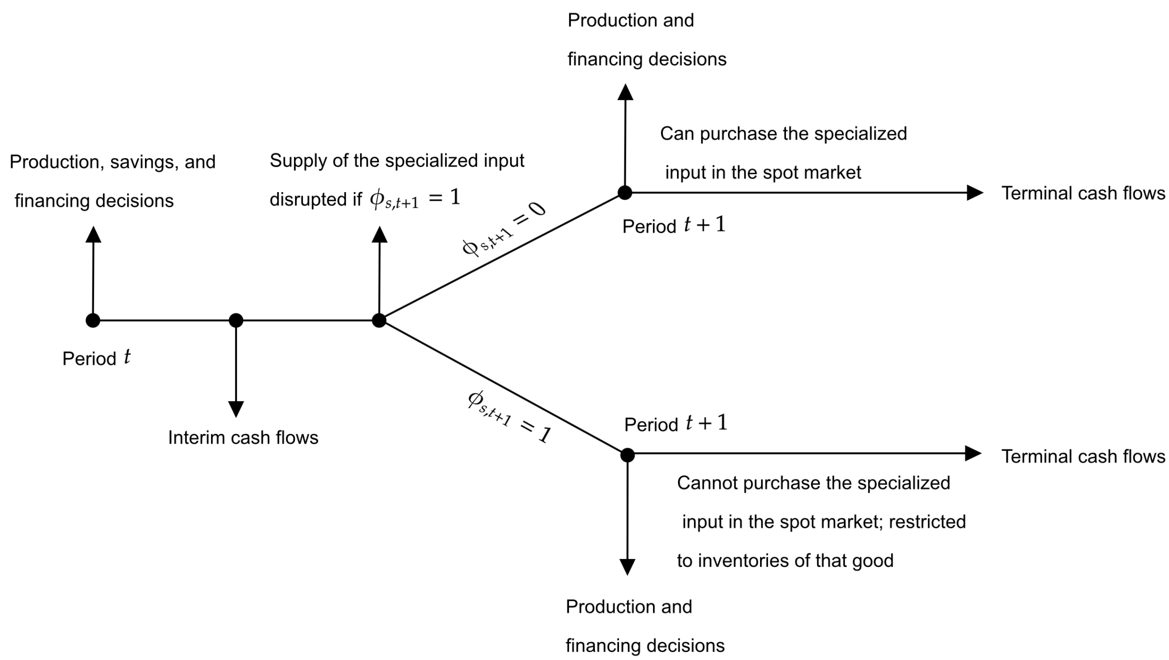


Figure 1: Model timeline
This figure shows a timeline of the model.

the cash reserves to hold (C_t), and the amount of debt to raise (B_t). Given input utilization ($N_{g,t} = P_{g,t} - i_{g,t}, N_{s,t} = P_{s,t} - i_{s,t}$), the firm generates interim cash flows by the end of period t, which are subject to a cash flow shock z_t. The firm's manager knows the distribution of z_t, but does not observe the realization of z_t when making decisions at the beginning of period t. The firm's revenue is determined by a Cobb-Douglas production function:[8]

$$F(z_t, N_{g,t}, N_{s,t}) = z_t N_{g,t}^{\theta_g} N_{s,t}^{\theta_s} \tag{1}$$

where $\theta_g + \theta_s < 1$ so that there are decreasing returns to scale.

In period $t+1$, the firm's decisions are limited to the procurement of inputs ($P_{g,t+1}, P_{s,t+1}$) and debt issuance (B_{t+1}). Given its two-period lifespan, the firm neither accumulates savings nor retains inventories during this final phase. As previously noted, the supply network of the specialized input

[8] 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 of limited substitutability across inputs during supply network disruptions (e.g., Boehm, Flaaen, and Pandalai-Nayar, 2019).

is disrupted when $\phi_{s,t+1} = 1$, which precludes sourcing specialized inputs from the spot market. Consequently, specialized input utilization is determined by the input purchases in period $t+1$, subject to any supply network disruptions, and by the inventories held from period t net of carrying costs $\alpha \in (0,1)$ (i.e., $N_{g,t+1} = P_{g,t+1} + (1-\alpha)i_{g,t}$ and $N_{s,t+1} = (1-\phi_{s,t+1})P_{s,t+1} + (1-\alpha)i_{s,t}$). As before, the firm produces cash flows at the end of period $t+1$, subject to cash flow shock z_{t+1}.

2.3 Financing frictions and supply network fragility

The firm finances its period $t+1$ input purchases using the cash flows realized at the end of period t, cash reserves carried over from period t, and from 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 that the firm incurs quadratic financing costs ($\frac{1}{2}\lambda_t B_t^2$) for each dollar of debt raised. These financing frictions can be attributed to various 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 for each period, thereby preventing the firm from reaching the optimal level of production that would be feasible in the absence of financial frictions.

In recent models of production network formation, supply network fragility emerges in equilibrium either when the supply of specialized intermediate inputs becomes concentrated in a few suppliers or when technology shocks expand the set of input options available to firms, making production more complex (Oberfield, 2018; Acemoglu and Azar, 2020; Acemoglu and Tahbaz-Salehi, 2020). Consequently, disruptions within these specialized supply networks or constraints on firms' production due to interdependencies of required inputs can pose substantial risks. Elliott, Golub, and Leduc (2022) characterize a supply network as fragile when output is susceptible to shocks. They demonstrate that the sensitivity of production to supply network disruptions depends on the degree of input specialization and the complexity of the production process. Building on these insights, I define supply network fragility (ρ_s) as the ex-ante probability that the supply network for specialized inputs will face disruptions, formally expressed as $\rho_s = \mathbb{E}_t \mathbb{P}(\phi_{s,t+1} = 1)$.

Note that disruptions characterized by $\phi_{s,t+1} = 1$ refer to scenarios where the sourcing of inputs is temporarily hindered, such as in a natural disaster or an idiosyncratic shock at a supplier's plant. These disruptions lead to an inability to source inputs from affected suppliers. It is important to differentiate these disruptions with situations like tariff increases, where the price of inputs may rise, but the firm can continue sourcing from the same supplier. In such cases, although the cost of procurement may increase, the supply network remains operational, allowing continuous sourcing albeit at higher prices.

2.4 Optimal policies

In period $t+1$, the firm's objective is to maximize the present value of the expected terminal value of equity to current shareholders, denoted as d_{t+1}:

$$V_{t+1} = \max_{\{P_{g,t+1}, P_{s,t+1}, B_{t+1}\}} d_{t+1} \tag{2}$$

subject to,

$$P_{g,t+1} + (1 - \phi_{s,t+1})P_{s,t+1} \leq W_{t+1} + B_{t+1} \tag{3}$$

$$B_{t+1} \leq B^*_{t+1} \tag{4}$$

where,

$$d_{t+1} = W_{t+1} + \mathbb{E}_{t+1}F(z_{t+1}, N_{g,t+1}, N_{s,t+1}) - P_{g,t+1} - (1 - \phi_{s,t+1})P_{s,t+1} - B_{t+1} - \frac{1}{2}\lambda_{t+1}B^2_{t+1} \tag{5}$$

$$W_{t+1} = F(z_t, N_{g,t}, N_{s,t}) + C_t, \tag{6}$$

$$N_{g,t+1} = P_{g,t+1} + (1 - \alpha)i_{g,t}, \tag{7}$$

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

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

Appendix B demonstrates that in the absence of supply network disruptions, the firm optimizes the purchase quantities of each input by equating expected marginal products to marginal costs.

Marginal costs comprise both marginal financing costs and the shadow value of debt capacity. If the supply network for the specialized input faces disruption, the firm is precluded from purchasing this input on the spot market. Consequently, production is constrained to the inventory of specialized inputs from period t, net of carrying costs. Under both scenarios, the firm's equity value at the end of period $t+1$ depends on resource constraints present at the beginning of that period.

The firm is deemed resource-constrained when its internal liquid assets, such as cash flows and reserves, fall short of covering the costs of input purchases in period $t+1$. Formally, this constraint is expressed as follows, where internal liquidity is defined in Equation 6:[9]

$$P_{g,t+1} + (1 - \phi_{s,t+1})P_{s,t+1} > W_{t+1} \tag{9}$$

The firm's resource constraints in period $t+1$ depend on a threshold value, denoted by 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. Using the specification of the production function in Equation 1, the definition of W_{t+1} in Equation 6, and Equation 9, I derive the threshold value of z_t and obtain the following expression:

$$\Omega = \frac{P_{g,t+1} + (1 - \phi_{s,t+1})P_{s,t+1} - C_t}{N_{g,t}^{\theta_g} N_{s,t}^{\theta_s}} \tag{10}$$

Let $\hat{d_{t+1}}$ 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. Then,

$$\hat{d_{t+1}} = \mathbb{E}_{t+1}F(z_{t+1}, \hat{N_{g,t+1}}, \hat{N_{s,t+1}}) - B_{t+1} - \frac{1}{2}\lambda_{t+1}B_{t+1}^2 \tag{11}$$

and

$$d^*_{t+1} = W_{t+1} + \mathbb{E}_{t+1}F(z_{t+1}, N^*_{g,t+1}, N^*_{s,t+1}) - P^*_{g,t+1} - (1 - \phi_{s,t+1})P^*_{s,t+1} \tag{12}$$

Since $\lambda_t > 0$ in Equation 11 and considering that the debt capacity constraint is binding, it follows that $\hat{d_{t+1}}$ is less than the unconstrained optimal equity value d^*_{t+1}. Consequently, the

[9] It is important to note that input inventories are excluded from the liquidity expression W_{t+1}. This is because input inventories, typically tailored to the firm's specific needs, are likely less valuable outside the firm than within, making them relatively illiquid (Shleifer and Vishny, 1991).

expected value of equity at the end of period $t+1$ for existing shareholders at the start of period t can be expressed as follows:

$$\mathbb{E}_t V_{t+1} = \int_{-\infty}^{\Omega} \hat{d_{t+1}} g(z) dz + \int_{\Omega}^{\infty} d_{t+1}^{*} g(z) dz \tag{13}$$

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.

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

$$\begin{aligned} V_t = \max_{\{P_{g,t}, P_{s,t}, i_{g,t}, i_{s,t}, C_t, B_t\}} & W_t - P_{g,t} - P_{s,t} - C_t - B_t - \frac{1}{2}\lambda_t B_t^2 \\ & + \mathbb{E}_t \left[\int_{-\infty}^{\Omega} \hat{d_{t+1}} g(z) dz + \int_{\Omega}^{\infty} d_{t+1}^{*} g(z) dz \right] \end{aligned} \tag{14}$$

subject to,

$$P_{g,t} + P_{s,t} + C_t \leq W_t + B_t \tag{15}$$

$$B_t \leq B_t^{*}, P_{g,t} \geq 0, P_{s,t} \geq 0, i_{g,t} \geq 0, i_{s,t} \geq 0, C_t \geq 0 \tag{16}$$

where,

$$N_{g,t} = P_{g,t} - i_{g,t} \tag{17}$$

$$N_{s,t} = P_{s,t} - i_{s,t} \tag{18}$$

In Appendix B, I derive expressions for the firm's period t optimal policies for inventory holdings and cash reserves, illustrating their role in mitigating the impact of potential future adverse cash flow shocks and supply network disruptions. First, I consider a benchmark scenario devoid of supply network fragility ($\rho_s = 0$). Subsequently, I investigate the scenario where the supply network of the specialized input is ex-ante fragile ($\rho_s \in (0, 1)$).

2.4.1 Benchmark

If the firm anticipates an adverse cash flow shock and increased financing costs in period $t+1$, it can mitigate the impact of these shocks by transferring resources from period t to period $t+1$. It can do so in two ways. First, the firm can purchase inventories in period t, incur the cost of carrying inventories, and have these inventories available for production in period $t+1$. Alternatively, the firm can save cash in period t, which can then be used to finance input purchases in period $t+1$. Proposition 1 demonstrates that in scenarios where supply network fragility is non-existent, the firm's optimal choice is to maintain cash reserves rather than inventories.

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

$$i^*_{g,t} = i^*_{s,t} = 0 \tag{19}$$

$$C^*_t > 0 \tag{20}$$

Proof: *See Appendix B.*

The model underscores two primary benefits of cash holdings in the absence of fragility. First, cash reserves alleviate resource constraints that may arise from tightened debt capacity or reduced interim cash flows following an adverse cash flow shock. Second, cash holdings enable firms to save on external financing costs. These precautionary and transactional motives for cash retention are well-established in economic theory and empirical research (e.g., Keynes, 1936; Baumol, 1952; Opler, Pinkowitz, Stulz, and Williamson, 1999; Almeida, Campello, and Weisbach, 2004).

It is not surprising that holding inventories is suboptimal without supply network fragility since the firm can instantaneously purchase inputs in every period, and the costs of carrying inventories exceed those of holding cash. These assumptions are justified by advancements in information technology, supply chain management, and lean manufacturing that have collectively reduced transportation costs and increased the effective cost of carrying inventories.[10] Therefore, Proposition 1 aligns with the trend of decreasing inventories and increasing cash balances among U.S. firms over the past three decades (Bates, Kahle, and Stulz, 2009; Gao, 2018).

2.4.2 Ex-ante supply network fragility

When the supply network of the specialized input is disrupted, a spot market for these inputs is unavailable in period $t+1$. In such circumstances, financial resources alone may not suffice for the firm to secure the necessary inputs for production. Proposition 2 examines the implications of ex-ante supply network fragility on the firm's optimal inventory and cash holdings.

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

$$i^*_{g,t} = 0 \tag{21}$$

$$\frac{\partial i^*_{s,t}}{\partial \rho_s} > 0 \tag{22}$$

$$\frac{\partial C^*_t}{\partial \rho_s} < 0 \tag{23}$$

Proof: *See Appendix B.*

Proposition 2 suggests that as the fragility of the supply network for specialized inputs increases, the firm's optimal policies shift towards increasing specialized input inventories and reducing cash reserves. This adjustment reflects a change in the relative marginal benefits of cash and inventories as hedging tools. Specifically, increased fragility reduces the marginal utility of cash by limiting its effectiveness as an ex-ante hedge against future shocks. This is because the firm cannot acquire specialized inputs from the spot market during disruptions. In such scenarios, cash holdings are beneficial primarily in addressing the ex-post consequences of specialized input disruptions rather than ensuring uninterrupted production. In contrast, maintaining inventories of specialized inputs

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

emerges as a more effective hedge against fragility, as it guarantees the firm's operational continuity and cash flow generation during disruptions.

It is crucial to acknowledge that hedging future shocks is costly as it entails forgone investment. The firm, therefore, optimally allocates its hedging resources. The model's predictions are particularly relevant in scenarios where an increase in the fragility of specialized inputs or a shift in production processes towards those more reliant on such inputs triggers a substitution effect in hedging strategies, shifting the focus from cash to inventories.

It is also important to recognize that cash reserves still retain their value in mitigating the impact of general cash flow shocks that could hinder the procurement of generic inputs. Therefore, while the optimal cash balance is predicted to decrease in response to heightened fragility, it should not fall to zero. This maintained level of liquidity reflects the ongoing need for firms to manage potential risks associated with sourcing generic inputs, underscoring the balanced approach firms must take in allocating resources to mitigate various risks.

Lastly, the model suggests that a firm's financial leverage may change due to supply network fragility. According to Equation 15, the amount of debt raised in period t is a function of the difference between input purchases and cash savings, net of the initial endowment. Consequently, the model predicts that debt issuance increases if the increase in input purchases in response to supply network fragility exceeds the reduction in cash holdings. As shown in Appendix B, the marginal utility of inventory holdings increases non-linearly with the probability of disruptions in the supply network for specialized inputs, which suggests that the increase in purchases of specialized inputs to maintain inventories will surpass the contraction in cash reserves as supply network disruptions become more likely or severe.

The foundational assumption in these findings is the absence of spot markets for specialized inputs post-disruption, which merits further elaboration. This assumption reflects scenarios where inputs are so specialized that a firm cannot source them from alternate suppliers at any cost after a disruption. Both data and anecdotal evidence suggest that specialized inputs with these characteristics are prevalent. For example, Section 3.3 reveals that over 20% of the sample firms' inputs are sourced exclusively from a single global supplier. Similarly, scarce raw materials, especially those concentrated in specific regions, are also examples. These include rare earth elements and cobalt, essential in various high-tech applications, and significantly concentrated in countries like China and the Democratic Republic of Congo respectively.[11]

However, even when alternative suppliers exist, the costs associated with switching can be prohibitive (e.g., Antràs, 2003; Antràs, Fort, and Tintelnot, 2017), effectively barring firms from tapping into these alternatives. In particular, when switching costs surpass the costs of carrying inventories, maintaining reserves of specialized inputs is still the optimal strategy to preemptively hedge against supply network fragility.

3 Data

This section describes the global supply network data and other data used in the empirical analysis. It also presents stylized facts about sample U.S. manufacturing firms' global supply networks and defines empirical metrics for assessing supply network fragility.

3.1 Sample construction

I start with a list of U.S. publicly listed manufacturing firms with Standard Industrial Classification (SIC) codes ranging between 2000 and 3999, obtained from Compustat, from 2007 to 2021. I require firms to have non-missing total assets, sales, and at least three years of consecutive data, which yields 2,346 unique manufacturing firms during the given period. Out of this set, the study concentrates on the 895 firms with global supply networks identified by their imports from foreign suppliers. The import data used in this analysis comes from two vendors: ImportGenius and Panjiva. They provide daily records of U.S. firms' maritime imports since July 2007, including detailed information on product descriptions, supplier identifiers, and logistical details such as ports and shipping vessels. In the analyses, I consider several quantity measures of import intensity, including import volume, shipment counts, and import weight. Import volume is measured in twenty-foot equivalent units (TEUs), corresponding to the volume occupied by a typical container

[11] See, for instance, "Rare Earths, Scarce Metals, and the Struggle for Supply Chain Security," *Foreign Policy Research Institute*, March 30, 2022.

in a cargo ship, while weight is measured in metric tons.[12]

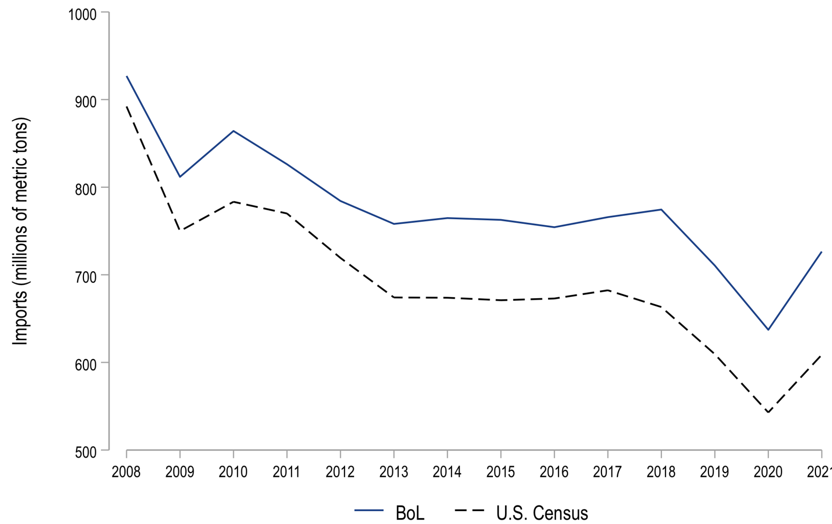
Both ImportGenius and Panjiva derive their information from bill of lading (BoL) documents, which are collected by the CBP.[13] Each dataset, however, has distinct features that provide unique insights. ImportGenius, for instance, offers granular data that includes details from both the master bill of lading (issued by the carrier to the supplier) and the house bill of lading (issued to the recipient). This distinction is crucial because the master bill often lists the carrier as the supplier, whereas the house bill accurately identifies the actual supplier. Panjiva, on the other hand, predominantly utilizes the master bill of lading but compensates with unique identifiers for a subset of suppliers, facilitating the tracking of supplier relationships across firms and time.[14] Importantly, the dataset also delineates parent-subsidiary relationships among suppliers. I consider the ultimate parent as a firm's supplier, which alleviates concerns that fragility might be understated when an input is available from multiple suppliers under the same parent company.

Appendix C presents several stylized facts about U.S. manufacturing firms' global supply networks, as inferred from the BoL data. It illustrates that imports predominantly consist of raw materials and intermediate goods rather than finished products. The data also uncovers a significant concentration of suppliers, with China alone accounting for 31% of them in 2021. Furthermore, Appendix C highlights the diversity and complexity of input-supplier relationships. It shows that many specialized inputs are sourced from a limited number of global suppliers and, in some cases, a singular supplier. This underscores the potential fragility of supply networks due to reliance on a narrow supplier base for specific inputs.

In addition to data on global supply networks, I obtain financial data from Compustat, 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 on selected Chinese goods from the U.S. International Trade Commission (USTC).

[12] Import value is not available in the BoL data.
[13] Appendix C shows an example of a BoL form.
[14] Panjiva's dataset includes unique identifiers for 35% of suppliers. I assigned unique identifiers to the remaining suppliers using a textual algorithm that accounts for typographical errors in matching supplier names. The accuracy of these matches was verified by manually comparing the names of a random sample of suppliers. Further details are provided in Appendix C.

Figure 2: Aggregate maritime imports: U.S. Census Bureau vs. BoL data
This figure compares the evolution of aggregate maritime imports in millions of metric tons in the U.S. Census Bureau data and the bill of lading (BoL) data collected by Panjiva and ImportGenius from 2008 to 2021.



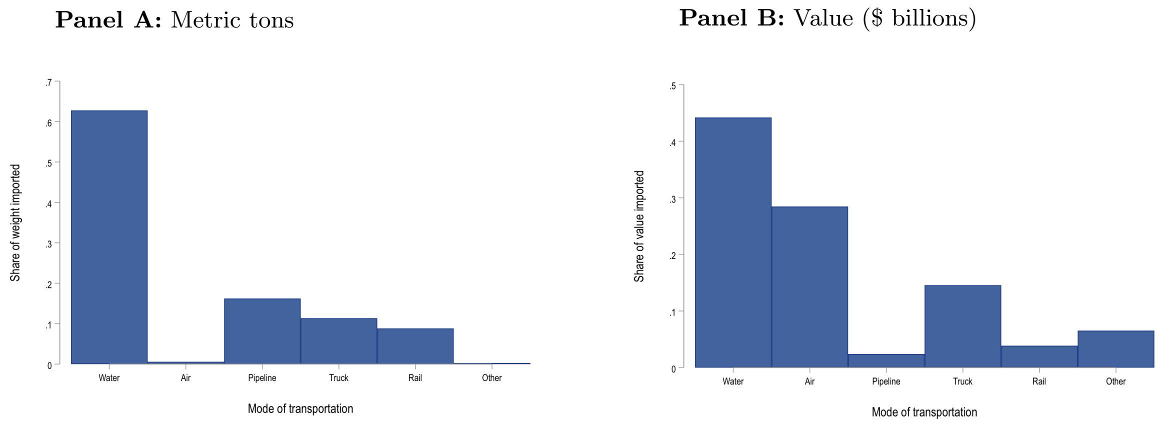
3.2 Data quality and coverage

Given the novelty of the BoL data in finance research and its specific focus on maritime supplier networks, it is important to validate the quality of the data and ensure they accurately reflect firms' global supply networks. To this end, I compare the evolution of import weight, measured in millions of metric tons, from the BoL data against figures from the U.S. Census Bureau from 2008 to 2021. As illustrated in Figure 2, there is a remarkable congruence between the two datasets since 2008, notwithstanding some differences in levels attributable to the exclusion of North American Free Trade Agreement (NAFTA)-related imports in the U.S. Census Bureau data. Furthermore, the BoL data has been shown to be comparable to confidential administrative datasets like the U.S. Census Bureau Longitudinal Firm Trade Transactions Database (LFTTD).[15] Therefore, the BoL data not only matches the comprehensiveness and quality of the U.S. Census Bureau information on maritime imports but also offers additional granularity and distinctive insights into the characteristics of firms' inputs and suppliers.

One way to assess the representativeness of global supply networks inferred from the BoL data

[15] See Flaaen, Haberkorn, Lewis, anderson Monken, Pierce, Rhodes, and Yi (2023) for a comparison of the Panjiva BoL data and LFTTD.

Figure 3: U.S. international trade by mode of transportation
This figure shows the fraction of U.S. imports in 2021 by mode of transportation (Water, Air, Pipeline, Truck, Rail, and Other) with weights proportional to metric tons (Panel A) and value (Panel B). These data are from the U.S. Department of Commerce, U.S. Census Bureau, and U.S. Department of Transportation.



is to examine the proportion of global imports conducted via maritime shipments. To this end, I computed the proportion of total imports in 2021 by different transportation methods, drawing on data from the U.S. Department of Commerce, the U.S. Census Bureau, and the U.S. Department of Transportation. Figure 2 presents these proportions.

Panel A indicates that maritime shipments accounted for 63% of all imports by weight, with air shipments comprising less than 1% and no other mode surpassing 20%. Conversely, Panel B, which assesses import value, attributes 44% of total imports to maritime transport, with air and truck shipments representing 28% and 15%, respectively, and no other method exceeding 10%.

Appendix C confirms the stability of these proportions since the early 2000s. The dominance of maritime transport in U.S. international trade supports the premise that supply networks derived from BoL data reflect actual global supply networks. Further, Appendix C includes analyses that reveal a consistent composition of Harmonized System (HS) codes, an internationally standardized system of names and numbers to classify traded products, across import modes. Specialized imports such as electrical components and machinery account for about one-third of total imports in the top ten HS codes across maritime and air imports. This consistency suggests that focusing on maritime imports does not neglect any critical elements of supply network fragility related to the nature of imported inputs.

3.3 Empirical measure of supply network fragility and descriptive statistics

The empirical analysis aims to test the hypotheses introduced at the end of Section 2. Therefore, I construct an empirical measure of supply network fragility that captures the notion of fragility in the model. As defined in the introduction, supply network fragility is the ex-ante likelihood that supply network disruptions hamper a firm's production capabilities. This concept is quantified in Section 2 by the parameter ρ_s, which represents the expected probability of a disruption in the supply of specialized inputs, denoted as $\mathbb{E}_t\mathbb{P}(\phi_{s,t+1} = 1)$.

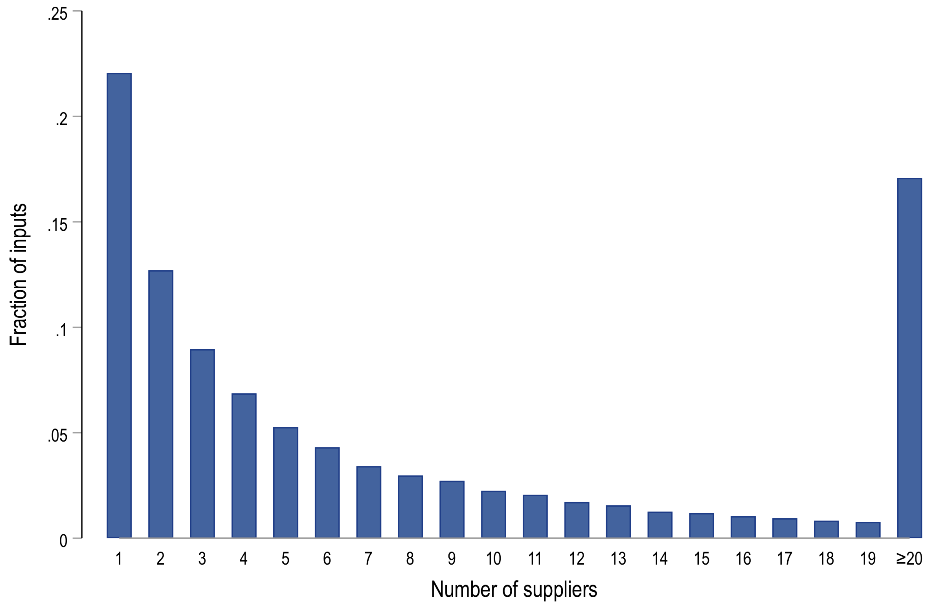
In practical terms, supply network fragility (ρ_s) can be written as the product of the ex-ante likelihood of supply network disruptions and pre-existing characteristics of inputs and suppliers that exacerbate the impact of such disruptions for firms:

$$\underbrace{\rho_s}_{\text{Fragility}} = \underbrace{\rho_c}_{\text{Characteristics}} \cdot \underbrace{\rho_d}_{\text{Disruptions}} \tag{24}$$

Using the above equation, I can exploit variation in the ex-ante characteristics of inputs and suppliers to estimate the impact of supply network fragility on corporate policies. As discussed in Section 2.3, a significant contributor to supply network fragility in recent models of supply network formation is the specialization of inputs and their concentration among a few suppliers (Acemoglu et al., 2012; Oberfield, 2018; Acemoglu and Azar, 2020; Elliott, Golub, and Leduc, 2022). In addition to being firmly rooted in theory, this concept of supply network fragility is also evident in the empirical data. For example, Figure 4 depicts the distribution of inputs firms use according to the number of available suppliers. The figure shows that, strikingly, over 20% of inputs are available from a single global supplier, highlighting the potential fragility of these supply networks.

The empirical evidence is bolstered by anecdotal evidence highlighting the risks associated with highly specialized inputs sourced from a limited number of suppliers. A case in point is the global supply of neon gas and palladium, which are critical for semiconductor and chip manufacturing and predominantly sourced from Russia and Ukraine. The ongoing conflict between these two countries has prompted companies reliant on these inputs to build up inventories, anticipating potential supply network disruptions. The underlying rationale is that finding alternative suppliers for these

Figure 4: Fraction of inputs by the number of suppliers
This figure shows the fraction of inputs sourced by firms by the number of suppliers providing those inputs. The sample comprises 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. Global supply network data are from ImportGenius and Panjiva.



specialized inputs would be not only time-consuming but also prohibitively expensive, particularly as the few alternatives may also be exposed to geopolitical tensions of their own, such as those in China.[16] Given these considerations, my analysis focuses on the scarcity of suppliers as a key ex-ante characteristic that contributes to the fragility of a firm's supply network.

To construct a firm-year empirical proxy of supplier scarcity, I first define a vector whose elements contain the number of alternative suppliers for each input j (where $j \in (1, \ldots, J)$) used by firm i in year t. This vector is denoted as $S_{i,j,t} = (S_{i,1,t}, S_{i,2,t}, \ldots, S_{i,J,t})$. More precisely, S_{ijt} indicates the number of alternative suppliers in the data from which other firms, denoted as k (where $k \neq i$), source input j, excluding the current supplier of input j for firm i at time t. Next, I weight each element of that vector by the lagged import volume of each product W_{ijt-1}.[17] Supplier scarcity is then defined as the additive inverse of the weighted number of alternative suppliers of

[16] See "Russian Attack on Ukraine Could Dent Chip-Maker Supply Lines," by Suman Bhattacharyya, February 25, 2022, *The Wall Street Journal*.
[17] In Appendix D, I show that the results in Section 4 are robust to constructing this variable using weights proportional to shipment counts.

firm i in year t, divided by 100 to facilitate the interpretation of coefficient estimates.

In Appendix C, I present anecdotal evidence suggesting the supplier scarcity measure captures important aspects of supply network risk. For instance, the ten firms identified as having the most fragile supply networks, per this measure, produce highly specialized products across diverse industries. These products likely rely on equally specialized inputs. Among them is a firm specializing in designing and manufacturing state-of-the-art computing modules and systems tailored for AI transportable devices. Another company on the list develops advanced communication equipment. Additionally, several firms in this group belong to the healthcare sector, pioneering the creation of niche medical devices and materials. Notably, one of these companies emphasized in the "Nature of Operations" section of its latest 10-Q financial report that supply chain risk is an important consideration for the firm's business.

In line with the anecdotal evidence, Appendix C reveals a strong correlation between supplier scarcity and textual indicators of supply network risk. Specifically, using a method similar to that of Hassan, Hollander, van Lent, and Tahoun (2019), the analysis demonstrates that firms facing greater supplier scarcity use terms associated with supply network fragility near keywords like "risk" and "uncertainty" more frequently in their financial reports. Furthermore, the language in these reports tends to be contextually similar to broader discussions of supply network fragility.

Table 1 shows descriptive statistics on global supply networks (Panel A) and accounting characteristics (Panel B) for the firm-year panel of 895 publicly listed U.S. manufacturing firms from 2007 to 2021. During this period, the median firm received 210 shipments and 294 TEUs annually. However, the distribution of imports is markedly skewed as the average firm received 1,069 shipments and 2,200 TEUs. These firms typically import a diverse array of products from an extensive network of suppliers across multiple countries. For example, the median firm procured 23 distinct products from 20 suppliers in nine countries.

Despite this heterogeneity, the weighted average number of alternative suppliers for the median firm is 2.83, suggesting that firms have a limited selection of suppliers for some inputs. However, there is also skewness in this measure as the average is higher at 11.38. Skewness in the number of alternative suppliers is driven by imports of non-specialized machinery components such as

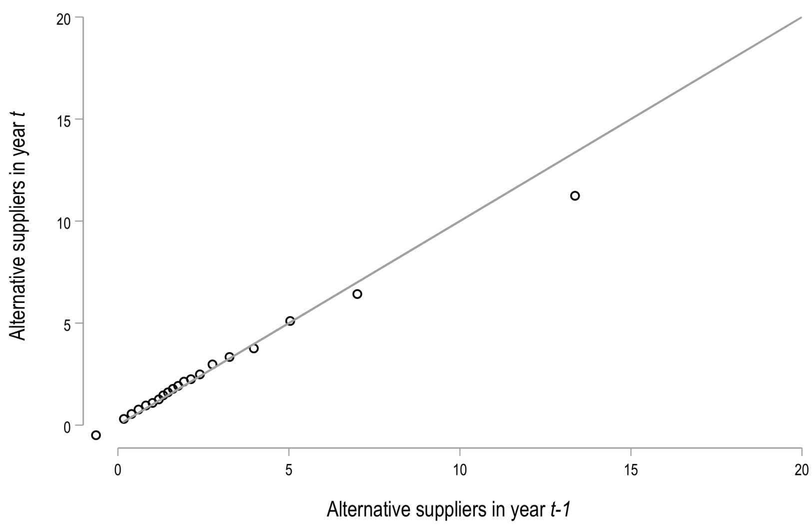
Table 1: Summary Statistics
This table reports summary statistics on global supply networks (Panel A) and accounting characteristics (Panel B). The sample is a firm-year panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. Appendix A presents variable definitions.

	Obs.	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Supply networks						
Import volume (TEU)	10,139	2,201.81	6,198.75	34.95	294.26	1,544.92
Number of import countries	10,139	11.38	8.89	4.00	9.00	17.00
Number of lading ports	10,139	18.11	16.79	5.00	13.00	26.00
Number of products	10,139	43.55	56.44	8.00	23.00	58.00
Number of shipments	10,139	1,069.29	2,751.68	38.00	211.00	918.00
Number of suppliers	10,139	43.01	64.49	6.00	20.00	53.00
Number of unlading ports	10,139	8.89	6.15	4.00	8.00	13.00
Supplier scarcity	10,139	−0.11	0.27	−0.09	−0.03	−0.01
Weighted number of alternative suppliers	10,139	11.38	27.37	1.10	2.83	8.70
Panel B: Accounting characteristics						
Assets ($billions)	10,139	5.95	13.72	0.35	1.26	4.33
Total debt/assets	10,139	0.24	0.19	0.07	0.22	0.35
Cash/assets	10,139	0.16	0.16	0.05	0.11	0.22
Cash flow/assets	10,138	0.10	0.15	0.08	0.12	0.16
Capex/assets	10,135	0.03	0.03	0.02	0.03	0.04
Cost of goods sold/assets	10,139	0.66	0.42	0.36	0.57	0.86
Input inventories/assets	10,139	0.07	0.07	0.02	0.06	0.10
Market-to-book ratio	10,136	3.21	6.04	1.35	2.25	3.77
R&D/sales	10,109	0.09	1.06	0.00	0.02	0.06

bearings, gears, belts, and bolts, as well as textiles and some plastics, which are available from a broader supplier base. As previously mentioned, supplier scarcity is simply the weighted number of alternative suppliers multiplied by minus one and divided by 100 for interpretative convenience.

Panel B of Table 1 reveals that the median book leverage and cash-to-assets ratio for sample U.S. manufacturing firms were 22 and 11 percent, respectively, from 2007 to 2021. These firms generally display less financial flexibility than their counterparts in the unrestricted Compustat sample, where median book leverage and cash-to-assets ratios were 15 percent and 18 percent, respectively. Moreover, the firms in the sample are larger, more profitable, and maintain significantly higher inventory levels than those in the broader Compustat dataset. To illustrate, the median value of input inventories relative to assets is six percent in the sample, in stark contrast to a median value of zero in the unrestricted dataset.

Figure 5: Persistence of the number of alternative suppliers
This figure shows a binscatter plot of the firm-level weighted average number of alternative suppliers across a firm's inputs, with weights proportional to lagged import volumes, in years t (y-axis) and $t-1$ (x-axis). Industry fixed effects are included. The sample consists of 895 publicly listed U.S. manufacturing firms with global supply networks. Global supply network data are from ImportGenius and Panjiva.



4 Supply network fragility and corporate policies

I begin analyzing the relation between supply network fragility and corporate policies by estimating firm-year panel regressions of the following model:

$$Y_{it} = \alpha_j + \alpha_t + \beta_1 Supply\ network\ fragility_{it-1} + \beta_X X_{it-1} + \epsilon_{it} \quad (25)$$

where i indexes firms, j represents two-digit SIC industries, and t denotes years. I present results from various specifications of Equation 25, where Y_{it} is input inventories over assets, cash over assets, or book leverage. The term *Supply network fragility* refers to the supplier scarcity measure defined in Section 3.3. Figure 5 presents a binscatter plot that visualizes the firm-level count of alternative suppliers for a firm's inputs in years t and $t-1$. This illustration indicates that the number of alternative suppliers, and consequently supplier scarcity, is highly persistent within firms, as the measure's year-over-year correlation closely aligns with the 45-degree line. The enduring nature of supplier scarcity is unsurprising, as it is likely predominantly shaped by persistent production processes, especially over short horizons. In light of this, the impact of supply network fragility on firm policies is estimated from cross-sectional variation across firms, within and across industries.

I employ two estimation approaches. Initially, I estimate panel regressions of Equation 25 with different combinations of industry (α_j) and year fixed effects (α_t) in a firm-year panel. For these regressions, standard errors are clustered at the firm level. Subsequently, I estimate cross-sectional regressions in a dataset that comprises one observation per firm, with variables averaged within each firm over the years. Standard errors in these regressions are robust to heteroskedasticity. In both approaches, the vector X includes controls for standard determinants of inventories, cash, and leverage policies, as highlighted in the literature (e.g., Bates, Kahle, and Stulz, 2009). These determinants include market-to-book ratios, firm size, research and development expenditures, cash flows, and capital expenditures. Table 2 present the results of these panel and cross-sectional regressions.

The findings in columns (1) through (4) of Panel A suggest that higher supplier scarcity is associated with higher inventory holdings and lower cash holdings. These results are highly statistically and economically significant. For instance, the estimated coefficients in columns (1) and (3) imply that a one standard deviation increase in supplier scarcity corresponds to a 6.6% increase in input inventory holdings and a 13.3% decline in cash over assets relative to their mean values. Furthermore, the coefficient estimates of the impact of supplier scarcity on book leverage in columns (5) and (6) are also positive and significant. When industry fixed effects are included in columns (2), (4), and (6), the coefficient estimates remain virtually identical to those without these fixed effects in columns (1), (3), and (5). This suggests that the cross-sectional variation between firms outweighs variation across industries for the impact of supply network fragility on firm policies.

The results in Panel B, estimated exclusively from cross-sectional variation across firms, align with those in Panel A but are larger in magnitude. Specifically, one standard deviation higher supplier scarcity is associated with 11% higher input inventory holdings, 16.8% lower cash holdings, and 4.9% higher book leverage. Collectively, these findings substantiate the hypotheses posited at the end of Section 2. These hypotheses suggest that it is optimal for firms to hold relatively more

Table 2: Supply network fragility and corporate policies

This table reports results from regressions of U.S. manufacturing firms' financial policies and inventory holdings on supplier scarcity, an ex-ante measure of supply network fragility. The sample is a firm-year panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. Panel A presents panel regressions with different sets of fixed effects for two-digit SIC industries and years. Panel B presents cross-sectional regressions where all variables are within-firm averages from 2007 to 2021. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. t-statistics based on standard errors clustered at the firm level (Panel A) or robust to heteroskedasticity (Panel B) 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: Panel regressions

	Input inventories/assets		Cash/assets		Total debt/assets	
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier scarcity$_{t-1}$	0.017***	0.018***	−0.079***	−0.072***	0.030**	0.025**
	(2.876)	(3.095)	(5.877)	(5.426)	(2.094)	(2.535)
Market-to-book ratio$_{t-1}$	−0.000**	−0.000	0.002***	0.002***	0.001	0.001
	(2.565)	(1.275)	(4.198)	(4.260)	(0.665)	(0.911)
Ln(Assets)$_{t-1}$	−0.013***	−0.013***	−0.014***	−0.011***	0.036***	0.033***
	(10.756)	(10.897)	(5.997)	(4.607)	(12.279)	(30.872)
R&D/sales$_{t-1}$	−0.002*	−0.002*	0.009	0.009	−0.003	−0.004
	(1.758)	(1.741)	(1.618)	(1.635)	(1.369)	(1.553)
Cash flow/assets$_{t-1}$	−0.010	0.001	−0.104***	−0.097***	−0.143***	−0.157***
	(0.671)	(0.076)	(2.771)	(2.622)	(3.052)	(6.347)
Capex/assets$_{t-1}$	−0.006	−0.007	−0.212**	−0.069	−0.092	−0.160**
	(0.111)	(0.135)	(1.978)	(0.633)	(0.593)	(2.167)
Fixed effects						
Industry	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,046	9,046	9,046	9,046	9,046	9,046
Adj. R^2	0.13	0.24	0.12	0.18	0.16	0.21

inventories of inputs compared to cash in response to fragile supply networks. In other words, these results are consistent with firms striking a balance between operational hedging through inventory accumulation and financial hedging through financial flexibility.

Additionally, the hypotheses posited at the end of Section 2 suggest that firm leverage should increase when the decrease in cash holdings is smaller in absolute value than the corresponding increase in specialized input purchases, which increase non-linearly as supply network disruptions become more likely. However, the empirical results in Table 2 indicate a more substantial decrease in cash holdings compared to the increase in input inventories. There are two plausible explanations for the observed divergence between theoretical predictions and the empirical results in Table 2.

Table 2: Supply network fragility and corporate policies (continued)
This table reports results from regressions of U.S. manufacturing firms' inventory holdings and financial policies on supplier scarcity, an ex-ante measure of supply network fragility. The sample is a firm-year panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. Panel A presents panel regressions with different sets of fixed effects for two-digit SIC industries and years. Panel B presents cross-sectional regressions where all variables are within-firm averages from 2007 to 2021. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. t-statistics based on standard errors clustered at the firm level (Panel A) or robust to heteroskedasticity (Panel B) 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: Cross-sectional regressions

	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)
Supplier scarcity	0.034***	−0.124***	0.051**
	(4.023)	(4.587)	(2.019)
Market-to-book ratio	−0.001***	0.007***	0.003**
	(2.788)	(4.792)	(2.040)
Ln(Assets)	−0.013***	−0.012***	0.033***
	(10.624)	(4.717)	(9.430)
R&D/sales	−0.004	0.013*	−0.006
	(0.920)	(1.765)	(0.734)
Cash flow/assets	−0.002	−0.208***	−0.119**
	(0.091)	(4.532)	(2.430)
Capex/assets	−0.049	−0.064	−0.202
	(0.561)	(0.340)	(0.832)
Fixed effects			
Industry	No	No	No
Year	No	No	No
Observations	895	895	895
Adj. R^2	0.13	0.25	0.13

First, the analysis relies on cross-sectional variation, which might not fully align with the dynamics of policy adjustments predicted by the model over time. When I examine dynamic changes in firm corporate policies in response to shocks to firms' anticipated risk of supply disruptions in Section 6.2, dynamic policy adjustments align quantitatively with the model's predictions. Specifically, leverage increases proportionally to the difference between input inventories and cash holdings. Second, cash levels are measured with high accuracy in the Compustat data, whereas inventories are subject to estimation error and accounting discretion. For instance, inventory levels reported in financial statements may not precisely match the volume of input purchases due to write-downs or changes in input prices (e.g., due to bulk orders following disruptions).[18]. Consistent with this, Section 6.2 also shows a much higher increase in input purchases than reflected in input inventory holdings when firms expected risk of supply network disruptions increases.

Appendix D provides additional evidence consistent with the findings in Table 2, along with robustness checks. First, it considers the inherent costs associated with inventory management, such as the need for storage space, which incurs rental and maintenance fees. Consequently, if supply network fragility necessitates higher inventory levels, this should logically lead to increased operating expenses. Supporting this, Table D1 reveals a positive relationship between supply network fragility and the cost of goods sold (COGS) and rental expenses.

Second, although the supplier scarcity metric is theoretically and empirically sound, I assess the robustness of the results to alternative measures of supply network fragility. In particular, Table D3 confirms that the influence of supply network fragility on corporate policies remains consistent when employing different measures. These alternative measures include the share of imports of intermediate goods, specialized electronic components, and scarce raw materials such as semiconductors and lithium—all of which suggest a high dependency on specialized inputs provided by a limited pool of suppliers. Additionally, the results hold when supply network fragility is gauged by the complexity of a firm's input mix, a factor that recent models have also identified as a contributor to supply network fragility (e.g., Elliott, Golub, and Leduc, 2022). Furthermore, Table D4 indicates that the results are similar when the supplier scarcity metric is constructed using shipment counts as weights rather than import volumes.

Third, a potential concern is that the COVID-19 pandemic may confound the results, as firms grappled with unprecedented supply and demand shocks that impacted their sourcing strategies and financial stability. Table D5 shows that the results are robust to excluding the COVID-19 pandemic years of 2020 and 2021 from the analysis. Relatedly, despite controlling for year fixed effects, errors may still be correlated across firms within years, especially if firms source inputs from suppliers in the same region. Although the number of year clusters is small, Table D5 also shows the results are robust to using standard errors clustered by both firm and year in the regressions

[18] See, for instance, Financial Accounting Standards Board. "ASC 330 - Inventory." FASB Accounting Standards Codification, 2023, available at: https://asc.fasb.org/topic&trid=2122428.

shown in Panel A of Table 2.

Finally, I examine the potential influence of not accounting for domestic suppliers within the global supply network data on the findings shown in Panel A of Table 2. If the supplier scarcity measure does not fully capture the supply networks of firms for whom domestic suppliers are a significant component, one might anticipate that the documented results would be predominantly driven by firms dependent on foreign suppliers for their inputs. To investigate this, I use Compustat segments data to determine the proportion of each firm's foreign suppliers as reported in their 10-K financial reports. This proportion is then interacted with the supplier scarcity measure. The results presented in Table D2 indicate that the estimated coefficients on the supplier scarcity variable are consistent with those in Panel A of Table 2, regardless of a firm's reliance on foreign versus domestic suppliers. This consistency mitigates the concern that excluding domestic supplier data from the supplier scarcity measure could introduce a bias in the results.

5 Omitted variables and reverse causality

There are important endogeneity concerns with the analyses presented thus far. For instance, it could be that firms with fragile supply networks are distinct in ways not captured or accounted for in the analysis or that there is a measurement error in the empirical measure of supply network fragility.

The direction of the bias, either away from or towards zero, depends on the correlations among the variables in question and the nature of the measurement error. Consider, for example, an omitted variable positively correlated with supply network fragility, but that has the opposite correlation with the outcome variables. The coefficient estimates would likely be biased toward zero in such a scenario. For instance, firms with fragile supply networks may be inherently innovative, and research suggests that such firms typically maintain higher cash reserves and have lower debt capacity (Bates, Kahle, and Stulz, 2009; Falato et al., 2022). If controlling for R&D expenditures does not fully capture the inherent innovativeness of firms with fragile supply networks, the coefficient estimates presented in Table 2 would be indeed biased towards zero. Similarly, classical measurement error that attenuates the observed relationship between supply network fragility and corporate policies would also result in a bias toward zero (Hyslop and Imbens, 2001).[19]

The literature emphasizes multi-sourcing, or contracting with multiple suppliers, as another strategy to mitigate supply network fragility (e.g., Elliott, Golub, and Leduc, 2022; Kopytov et al., 2022). Although this strategy might be challenging for firms dependent on specialized inputs from a limited pool of suppliers, it could raise reverse causality concerns. Specifically, firms facing financial constraints, with low cash-to-assets ratios and high leverage, may find it difficult to broaden their supplier base, potentially exacerbating their supply network fragility. In this case, the estimated coefficients in Table 2 would be biased away from zero. This would occur because the omitted variable, financial constraints in this instance, positively correlates with supply network fragility and influences corporate policies in the same direction as supply network fragility.

To address these concerns, I first use an IV strategy that leverages plausibly exogenous variation in supply network fragility during the sample period of 2007 to 2021, resulting from firms' adoption of technological advancements of the late 1980s and early 1990s that increased their reliance on specialized inputs. A salient characteristic of these inputs is their pronounced concentration among a limited number of global suppliers (Miller, 2022). Consequently, higher reliance on these inputs in manufacturing should increase supply network fragility.

In addition, I examine the empirical importance of the multi-sourcing mechanism in my dataset. Considering the substantial fixed costs associated with engaging new suppliers (Antràs, 2003; Antràs, Fort, and Tintelnot, 2017), firms may only consider diversifying their supplier base in response to disruptions expected to be long-lasting. To this end, I explore how firms adapted their sourcing strategies in reaction to the significant, persistent disruption caused by the U.S. tariffs on selected Chinese imports during 2018 and 2019.

5.1 Emerging technologies

The IV strategy hinges on the premise that certain technologies intensify the demand for specialized inputs. This increased demand can amplify the fragility of a company's supply network, given that

[19] However, if the measurement error in supply network fragility is correlated with its true value (a non-classical measurement error), the bias in coefficient estimates would be more complex. As discussed in Section 3.2 and Appendix C, relying on supply networks derived from BoL data does not appear to systematically overlook critical aspects of supply network fragility, potentially mitigating concerns about non-classical measurement error.

the supply of these specialized inputs tends to be concentrated in a few global firms (Miller, 2022).

I construct an instrument for supplier scarcity that captures firms' exposures to emerging technologies during the 1980s and 1990s through textual analysis of two novel data sources. The first data source is an archive of nearly 5,000 articles from Industry Week obtained from LexisNexis from 1986 to 1995, discussing emerging manufacturing technologies. Industry Week is recognized as a reputable source of information for managers in the manufacturing sector, offering insights into best practices, operations management, and, importantly, emerging technologies within the industry. The archival articles from Industry Week frequently discussed the implications and applications of new technologies such as computer systems, automation and robotics, and semiconductors, thus providing a rich textual dataset to identify key technologies of that period.

More specifically, I use the Industry Week articles to identify terms related to emerging technologies through a multi-step approach. I begin by extracting a list of uncommon words from articles discussing emerging technologies by comparing the word distribution in these articles against the Corpus of Contemporary American English (COCA).[20] A term from the Industry Week articles is deemed uncommon if it falls outside the top one thousand words typically found in magazine discourse, according to COCA's rankings.

In a subsequent step, I manually identified 100 unigrams and bigrams directly linked to specific technologies and materials from a random set of articles. The identified terms included "semiconductor," "laser," "chip," and "computer vision." With these terms as a foundation, I used a word embedding model, augmented with pre-trained vectors from Google News, to identify additional technologies that increase reliance on specialized inputs in the Industry Week archives. This model identifies terms that are contextually similar to the ones I had manually identified. I compiled a final list of 1,480 unique terms associated with emerging technologies from 1985 to 1995 using the expanded set of terms from the word embedding model. This extensive list allows for rich variation in firms' exposure to emerging technologies during the period.

In the final step, I use a "bag of words" methodology to quantify the occurrence of technology-

[20] COCA provides detailed estimates on the frequency of English words in different mediums. I focus on the frequency of words from over 100 magazines comprising over 80,000 texts from 1990 to 2019. The data are available at: `https://www.english-corpora.org/coca/`.

Table 3: List of technologies and materials
This table lists and describes a subset of the technologies and associated materials identified with textual analysis of Industry Week and firms' financial disclosure archives from 1986 to 1995.

Technology	Description	Materials	Description
(1)	(2)	(3)	(4)
Semiconductor	Material used in electronic circuits to control electrical current.	Polymer	Large molecules used for making plastics and resins.
Laser	Light amplification tool for cutting, aligning, or communication.	Silicon	Metalloid used in transistors and solar cells.
Chip	Compact unit containing electronic circuits used in computing devices.	Alloy	Mixed elements used to enhance metal properties.
Robot	Machine programmed to perform tasks autonomously.	Oxide	Oxygen compounds used in various technological applications.
Computer vision	Technology enabling computers to interpret visual information.	Polyethylene	Plastic used in packaging and containers.
RFID	Technology used for tracking and identification using radio waves.	Polypropylene	Polymer used in packaging, labeling, and textiles.
CNC	Technology for controlling machine tools with computers.	Carbide	Compound used for industrial cutting and drilling.
Sensor	Device detecting or measuring physical properties and signaling changes.	Polysilicon	Crystalline silicon used in solar and electronic industries.
Actuator	Device converting energy into motion to perform a task.	Ferrite	Ceramic material used in magnets, inductors, and microwave devices.
Wafer	Thin slice of semiconductor material used for the fabrication of integrated circuits.	Aramid	Heat-resistant synthetic fiber.

related terms in firms' financial reports from 1986 to 1995. This necessitates access to the textual content of financial disclosures from that era, a task complicated by the fact that such data became broadly accessible only after the SEC's EDGAR system went online in 1996. To overcome this challenge, I follow Guo and Jensen (2023) and manually compile the needed textual data for this analysis from Compact Disclosure CD-ROMs. These discs are a repository of text and tables extracted from 10-Ks and other filings dating back to 1986.[21] With this data, I compute the frequency with which each firm references emerging technologies that increase reliance on specialized

[21] Compact Disclosure was a pre-digital era database that provided financial information on publicly traded companies. It included financial documents like 10-Ks and other filings, offering both the latest and some past financial data for each listed firm.

inputs within the Management Discussion and Analysis (MD&A) section of their annual 10-K reports from 1986 to 1995. Table 3 lists and briefly describes some of the technologies and materials identified by the algorithm.

The instrument for supplier scarcity is defined as the average frequency of terms associated with the emerging technologies mentioned in firms' MD&A section of their 10-K financial reports from 1986 to 1995. To construct this instrument, a firm must have existed from 1986 to 1995 and be in my sample from 2007 to 2011. Given that only 486 of the 895 firms in the initial sample satisfy these conditions, I first replicate the findings presented in Section 4 using this reduced sample. The replicated baseline results and corresponding IV estimates are presented in Panels A and B of Table 4, respectively.[22]

The replicated results on the smaller sample in Panel A closely align with those in Panel A of Table 2, albeit the effect of supplier scarcity on book leverage is slightly less statistically significant. The first-stage results in column (1) of Panel B indicate a robust positive association between firms' technology adoption in the late 1980s and early 1990s, as captured by the frequency of technology-related terms in their financial reports, and contemporaneous supplier scarcity. Notably, the Kleibergen-Paap (KP) F-statistics in each of the models in columns (2) to (4) range from 143.07 to 154.45, far surpassing the critical thresholds for weak instruments suggested by (Stock and Yogo, 2005) and also exceeding the more stringent threshold of 104.7 recommended for a reliable five percent t-test in the recent IV inference literature (Lee et al., 2022).[23] The second-stage results in columns (2) to (4) support a causal interpretation of the findings in Table 2, suggesting that increased supply network fragility systematically causes higher input inventory levels, lower cash reserves, and higher book leverage.

The coefficient estimates presented in Panel B are approximately two to three times larger than those in Panel A. Considering the likelihood of classical measurement error and the presence

[22] For brevity, only results with year and industry fixed effects are shown in Table 4. The results excluding industry fixed effects, shown in Table D6, are similar. Moreover, the R^2 values are omitted from the second-stage results, as their interpretation in IV regressions deviates from that in standard Ordinary Least Squares (OLS) regressions. In IV regressions, unlike in OLS, the R^2 values do not signify the proportion of variance in the dependent variable that is accounted for by the independent variables.
[23] The first-stage point estimates reported in column (1) are the same across the models. However, the KP F-statistics differ slightly because each regression has a distinct error term associated with the dependent variable.

Table 4: Instrumental variables estimates

This table replicates the results from Table 2 on the sample of firms with requisite data for the instrumental variables (IV) estimation (Panel A) and from IV regressions that use a measure of firms' exposure to emerging technologies in the late 1980s and early 1990s as an instrument for supplier scarcity, an ex-ante measure of supply network fragility (Panel B). The sample is a firm-year panel of 486 publicly listed U.S. manufacturing firms with global supply networks and requisite data for the instrument from 2007 to 2021. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. *Technology adoption*$_{[1986,1995]}$ is the average frequency of terms related to emerging technologies mentioned in firms' Management Discussion and Analysis (MD&A) section of their 10-K financial reports from 1986 to 1995. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. All specifications include fixed effects for two-digit SIC industries and years. 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.

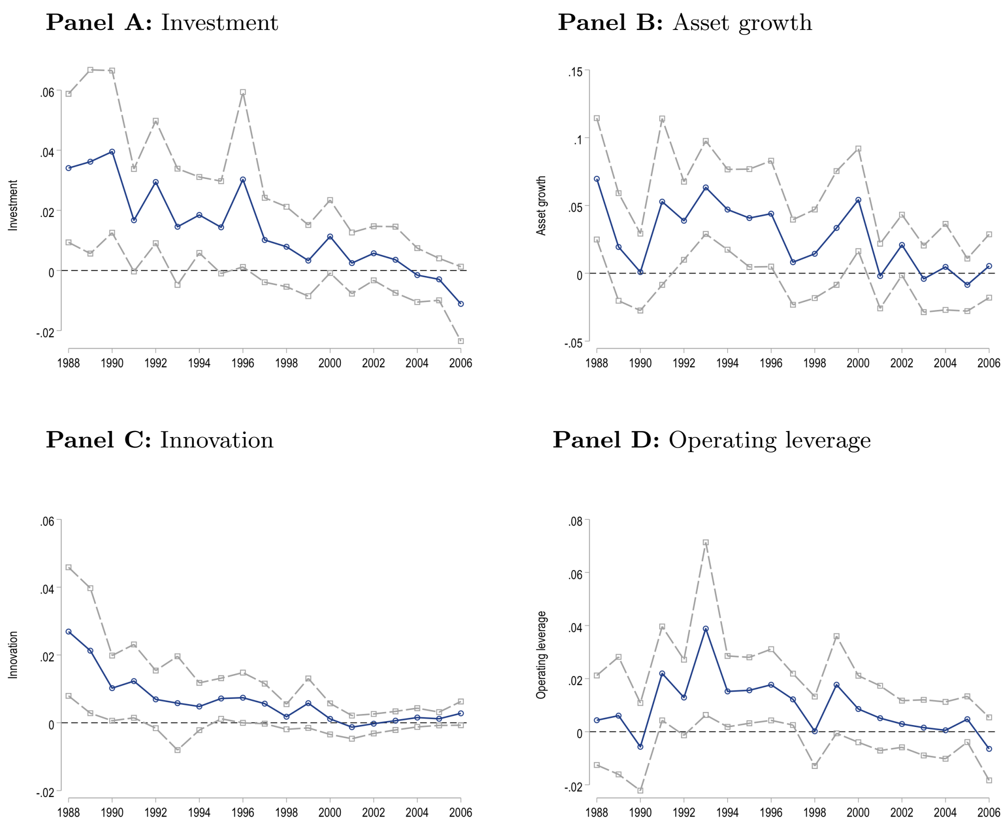
Panel A: Replicated baseline results			
	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)
Supplier scarcity$_{t-1}$	0.015***	-0.085^{***}	0.041*
	(2.807)	(3.744)	(1.893)
Controls	Yes	Yes	Yes
Fixed effects			
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	5,477	5,477	5,477
Adj. R^2	0.27	0.16	0.24

Panel B: IV estimates				
	First-stage	Input inventories/assets	Cash/assets	Total debt/assets
	Supplier scarcity	(1)	(2)	(3)
Technology adoption$_{[1986,1995]}$	0.120***			
	(12.427)			
Supplier scarcity$_{t-1}$		0.042**	-0.173^{***}	0.127***
		(2.482)	(4.359)	(2.771)
Controls	Yes	Yes	Yes	Yes
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	5,477	5,477	5,477	5,477
First-stage KP F-statistic		143.07	150.79	154.45
Adj. R^2	0.13			

of omitted variables, which, as previously discussed, are likely positively correlated with supply network fragility and negatively correlated with corporate policies, these larger coefficients in Panel B might more accurately represent the true causal effect of supply network fragility on corporate

Figure 6: Dynamic effects of technology adoption

This figure shows the estimated β coefficients (dark blue line) and 90% confidence intervals (light gray lines) from the following regressions: $Y_{it} = \alpha_i + \alpha_t + \beta \sum_{t=1988}^{t=2006} Technology\ adoption_{i[1986,1995]} \times Year_t + \epsilon_{it}$, where i indexes firms and t years. The sample is a firm-year panel of 486 U.S. manufacturing firms with global supply networks from 1987 to 2006. In Panels A, B, C, and D, Y_{it} is *Investment*, *Asset Growth*, *Innovation*, and *Operating leverage*, respectively. *Investment* is capital expenditures divided by lagged gross property, plant, and equipment (PP&E). *Asset growth* is year-on-year asset growth. *Innovation* is R&D expenditures divided by lagged assets. *Operating leverage* is selling, general, and administrative (SG&A) expenses divided by lagged total assets. *Technology adoption*$_{[1986,1995]}$ is the average frequency of terms related to emerging technologies mentioned in firms' Management Discussion and Analysis (MD&A) section of their 10-K financial reports from 1986 to 1995. The β coefficients capture the effect of *Technology adoption*$_{[1986,1995]}$ on the outcome variables each year from 1988 to 2006 relative to year 1987. α_i and α_t denote firm and year fixed effects, respectively. Standard errors are clustered at the firm level.



policies. However, it is also possible that the larger coefficients are indicative of estimating a local average treatment effect (LATE). More precisely, the LATE could reflect the impact of increased supply network fragility on firms more sensitive to technological changes, such as those in the high-tech manufacturing sector.

The validity of an instrument hinges on the exclusion restriction, which posits that the instru-

Table 5: Past technology adoption, investment, and operating leverage

This table reports results from regressions of U.S. manufacturing firms' investment, innovation, and operating flexibility on a textual measure of technology adoption from 1986 to 1995. The sample is a firm-year panel of 486 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Investment* is capital expenditures divided by lagged gross property, plant, and equipment (PP&E). *Asset growth* is year-on-year asset growth. *Innovation* is R&D expenditures divided by lagged assets. *Operating leverage* is selling, general, and administrative (SG&A) expenses divided by lagged total assets. *Technology adoption*$_{[1986,1995]}$ is the average frequency of terms related to emerging technologies mentioned in firms' Management Discussion and Analysis (MD&A) section of their 10-K financial reports from 1986 to 1995. These regressions control for lagged log assets, Tobin's q, and cash flows. 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.

	Investment	Asset growth	Innovation	Operating leverage
	(1)	(2)	(3)	(4)
Technology adoption$_{[1986,1995]}$	−0.005	−0.014	0.005	−0.009
	(1.127)	(0.979)	(1.316)	(0.723)
Controls	Yes	Yes	Yes	Yes
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	5,507	5,507	5,507	5,507
Adj. R^2	0.23	0.05	0.55	0.56

ment influences the dependent variable solely through the endogenous explanatory variable. Direct testing of the exclusion restriction is not possible. However, the research design narrows down the potential pathways through which the instrument might contemporaneously influence corporate policies. The underlying assumption is that adopting new technologies exerts a more lasting effect on the nature of production inputs than on corporate policies over extended periods. Therefore, although the initial adoption of new technologies might concurrently impact firm policies through alternative channels, such effects are expected to dissipate over time.

To assess the validity of the exclusion restriction, I estimate the effect of technology adoption in the 1980s and 1990s on several variables that could have a first-order influence corporate policies. For example, the integration of new technologies often necessitates investments in equipment and R&D, which could directly affect cash reserves and financial leverage (Bates, Kahle, and Stulz, 2009; Falato et al., 2022). Moreover, the adoption of such technologies may diminish operational flexibility by increasing fixed operating costs, and there is evidence linking operational flexibility to firm valuation, investment decisions, and capital structure (Detemple and Kitapbayev, 2017; Chen, Harford, and Kamara, 2019).

Figure 6 plots the estimated beta coefficients on interactions between *Technology adoption*$_{[1986,1995]}$ and year indicators from 1988 to 2006 on investment, asset growth, innovation, and operating leverage. Investment is gauged by the ratio of capital expenditures to the prior year's gross property, plant, and equipment (PP&E) and by asset growth. Innovation is assessed through R&D expenditures relative to lagged assets, while operating leverage is proxied by the ratio of selling, general, and administrative (SG&A) expenses to lagged assets, following Chen, Harford, and Kamara (2019). The beta coefficients capture the effect of technology adoption on these outcome variables from 1988 to 2006 relative to the excluded year 1987. The figure shows that while adopting new technologies has an immediate effect on these variables, such impact dissipates over time. For example, while adopting new technologies in the late 1980s and early 1990s had a statistically significant contemporary effect on investment and innovation, this effect was virtually zero by 2006. In Table 5, I estimate regression models of *Technology adoption*$_{[1986,1995]}$ on the same outcome variables during the sample period from 2007 to 2021 and find that none of the coefficients on the instrument to be statistically significant. Therefore, the instrument is unlikely to have a first-order effect on input inventory holdings, cash, and leverage policies through these alternative channels in the 2010s.

Another way to assess the validity of the exclusion restriction is to examine whether the instrument affects supplier scarcity through the hypothesized channel, namely that it persistently increases reliance on specialized inputs that contribute to fragile supply networks. Therefore, I estimate the impact of technology adoption during the late 1980s and early 1990s on the reliance on specialized inputs and generic inputs from 2007 to 2021. I classify imports into intermediate inputs or specialized electronic components and scarce raw materials using HS codes to measure specialized input utilization. For intermediate inputs, I use World Bank classifications.[24] For specialized electronic components and scarce raw materials, I use classifications by the U.S. Census Bureau and manual classifications following The White House (2021) report on building resilient

[24] In my sample, intermediate inputs per the World Bank definitions tend to be highly specialized. For instance, the most sourced HS code classified as an intermediate input corresponds to aircraft components.

Table 6: Past technology adoption and imports of specialized and generic inputs

This table reports results from regressions of U.S. manufacturing firms' imports of specialized and generic inputs on a textual measure of technology adoption from 1986 to 1995. The sample is a firm-year panel of 486 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Intermediate goods* is the share of import volume comprised of intermediate inputs in a year. *Advanced electronics* is the share of import volume comprised of advanced electronic components and scarce raw materials in a year. *Consumer goods* is the share of import volume comprised of consumer goods in a year. *Generic components* is the share of import volume comprised of components that are not classified as advanced electronics or scarce raw materials in a year. Imports are classified into intermediate and consumer goods and advanced electronics using Harmonized System (HS) codes. I follow World Bank classifications for intermediate and consumer goods and U.S. Census Bureau and manual classifications for advanced electronics and scarce raw materials. *Technology adoption*$_{[1986,1995]}$ is the average frequency of terms related to emerging technologies mentioned in firms' Management Discussion and Analysis (MD&A) section of their 10-K financial reports from 1986 to 1995. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. 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.

	Import share of specialized inputs		Import share of generic inputs	
	Intermediate goods	Advanced electronics	Consumer goods	Generic components
	(1)	(2)	(3)	(4)
Technology adoption$_{[1986,1995]}$	0.017***	0.028***	0.021	−0.024
	(2.868)	(3.999)	(1.096)	(1.237)
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	5,495	5,495	5,495	5,495
Adj. R^2	0.14	0.23	0.14	0.32

supply chains.[25] I classify imports as generic if they do not qualify as advanced electronics or scarce raw materials or if they are consumer goods intended for immediate use. The results in Table 7 reveal a significant positive correlation between the instrument and imports of specialized inputs in the 2010s but no significant correlation between the instrument and imports of generic inputs. This finding supports the hypothesis that earlier technology adoption has a lasting impact on firms' reliance on specialized inputs, contributing to the fragility of their supply networks.

I further explore the hypothesis that technology adoption augments reliance on specialized inputs for production by distinguishing between product and process innovations. Product innovation involves the creation of new or significantly enhanced products by incorporating new technologies, such as the introduction of GPS technology in vehicles in the late 1980s and early 1990s. Process

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

Table 7: Product vs. process innovations

This table reports results from regressions of U.S. manufacturing firms' imports of specialized inputs on textual measures of product and process technology adoption from 1986 to 1995. The sample is a firm-year panel of 486 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Intermediate goods* is the share of import volume comprised of intermediate inputs in a year. *Advanced electronics* is the share of import volume comprised of advanced electronic components and scarce raw materials in a year. Imports are classified into intermediate goods and advanced electronics using Harmonized System (HS) codes. I follow World Bank classifications for intermediate goods and U.S. Census Bureau and manual classifications for advanced electronics and scarce raw materials. *Technology adoption*$_{[1986,1995]}$ is the average frequency of terms related to emerging technologies mentioned in firms' Management Discussion and Analysis (MD&A) section of their 10-K financial reports from 1986 to 1995. In columns (1) and (2) *Technology adoption*$_{[1986,1995]}$ pertains to the product technologies, and in columns (3) and (4) to process technologies. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. 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.

	Product technologies		Process technologies	
	Intermediate goods	Advanced electronics	Intermediate goods	Advanced electronics
	(1)	(2)	(3)	(4)
Technology adoption$_{[1986,1995]}$	0.019**	0.021***	0.006	0.008*
	(2.408)	(3.514)	(1.011)	(1.841)
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	5,495	5,495	5,495	5,495
Adj. R^2	0.22	0.14	0.23	0.14

innovation, in contrast, pertains to introducing new or significantly improved methods for production or delivery. The shift to robotic assembly lines in manufacturing is an example of a process innovation.

The premise is that product innovations should be particularly conducive to a persistent reliance on specialized inputs since firms need those kinds of inputs for production. In contrast, while process innovations would require the firm to have more advanced machinery to make their products, these entail PP&E investment and should not directly increase the reliance on specialized inputs for production. That is, the supply network fragility associated with these components would be outsourced to the companies building the machinery used by the focal firm.

To examine this, I reconstruct the measure of technology adoption separately for product and process innovations. I identify product and process innovations by manually identifying a set of technologies associated with each category and then re-calibrating the word embedding model to identify these terms separately in the final list of terms obtained from Industry Week articles. Then, I construct the variable *Technology adoption*$_{[1986,1995]}$ as before but separately for each category of innovations. Table 7 presents the results of regressions similar to those in columns (1) and (2) of Table 6, but separately for product and process innovations. The results indicate that the increase in specialized input reliance resulting from adopting new technologies is primarily concentrated in those associated with product innovations.

5.2 Multi-sourcing and persistent disruptions

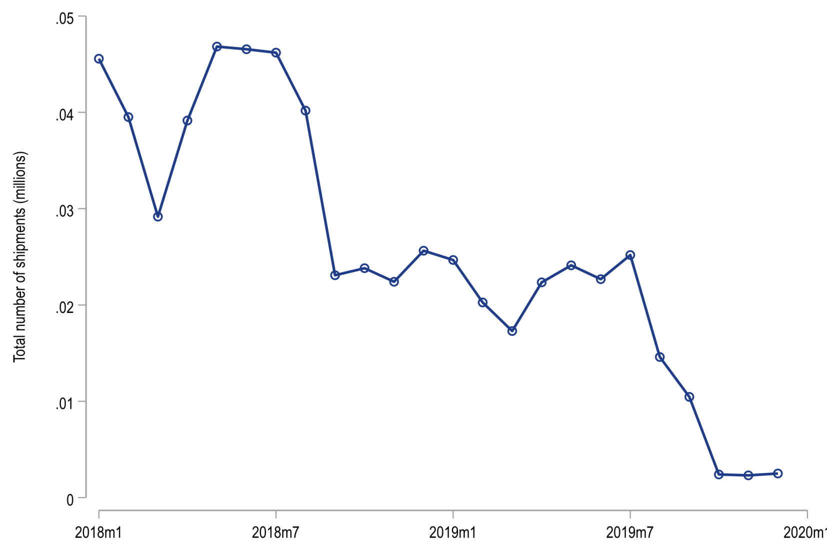
In this subsection, I examine the multi-sourcing strategy for reducing supply network fragility. The hypothesis is that firms may proactively set up contracts with multiple suppliers to mitigate the risk of input shortages due to supply network disruptions. Since sourcing from new suppliers likely entails fixed costs (Antràs, 2003; Antràs, Fort, and Tintelnot, 2017), only persistent shocks may encourage firms to switch. I thus investigate multi-sourcing around a significant and long-lasting shock: the introduction of U.S. import tariffs on selected Chinese goods during 2018 and 2019.

These tariffs were implemented in four waves between July 2018 to September 2019. The initial rounds in July and August of 2018 targeted 818 and 279 unique products, respectively. The subsequent rounds in September 2018 and September 2019 were more expansive, affecting nearly 9,000 products in total. The targeted items were predominantly specialized, including advanced machinery and high-tech components, aligning with the U.S. strategy to protect intellectual property and reduce technological reliance on China.[26] The aggregate effect of these tariffs on the imports of the targeted products was profound, as depicted in Figure 7. The number of shipments plummeted from a high of 46,000 in May 2018 to fewer than 3,000 by December 2019. This significant reduction shows the substantial impact of the tariffs and sets the stage for analyzing how firms adjusted their sourcing strategies in response to these persistent trade disruptions.

The enactment of these tariffs provides a valuable natural experiment to observe whether and how firms adapt their sourcing strategies in the face of prolonged supply chain challenges for two reasons. First, the median tariff increase, a substantial 25% across various stages, was particularly

[26] For example, see "Trump's China Fight Puts U.S. Tech in the Cross Hairs," by Cecilia Kang, September 23, 2018, *The New York Times*.

Figure 7: Aggregate impact of the 2018-2019 tariffs
This figure shows the total number of shipments of products originating from China affected by the 2018-2019 import tariffs from January 2018 to December 2019.



significant given that many of the targeted products had not been previously subject to tariffs. Second, to the extent that President Trump's election was unexpected, the tariff increases are plausibly exogenous (Amiti, Redding, and Weinstein, 2019). This aspect is crucial, as it addresses the common concern that tariff changes tend to be correlated with demand and supply shocks (Fajgelbaum, Goldberg, Kennedy, and Khandelwal, 2020).

I use a difference-in-differences methodology to estimate the impact of the tariff hikes on multi-sourcing. Given that the standard difference-in-differences estimator can exhibit significant bias when treatment timing varies across units (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 involves constructing a balanced panel dataset for each tariff wave, comprising the firms treated by the tariffs and those yet to be affected. This approach ensures that the estimated treatment effects are not contaminated by comparing firms treated at different times.

Treatment status is determined by whether firms imported an affected product from a Chinese supplier before the tariff rate increased. More precisely, a firm is considered treated if it imported a product with an eight-digit HS code specified in the tariff schedules released by the USTC from Chinese suppliers in the year preceding the tariff hike. Conversely, control firms are those that either did not import any of the listed products during the reference period or sourced them from non-Chinese suppliers. The stacked difference-in-differences analysis is conducted using the following regression model:

$$Y_{it} = \alpha_{ij} + \alpha_{tj} + \beta_1 Treated_i^j + \beta_2 Treated_i^j \times Post_t + \epsilon_{it} \tag{26}$$

where i represents firms, j denotes a specific tariff wave, and t refers to time, measured in months. The model is estimated within a symmetric twelve-month window surrounding each wave for the first three waves in July, August, and September 2018. However, for the fourth wave in September 2019, the estimation window is truncated to three months to avoid confounding effects that might arise from the onset of the COVID-19 pandemic. The dependent variable, Y_{it}, measures the quantity or volume of imports for the tariff-affected products sourced from suppliers outside of China. As a result, the model employs the Poisson pseudo-maximum likelihood (PPML) estimator, which is particularly suited for count data and remains unbiased in instances of zero-import firm-month observations (Silva and Tenreyro, 2006). To obtain an average treatment effect across the waves, the model includes firm×wave event and month×wave fixed effects, denoted by α_{ij} and α_{tj}. Standard errors are clustered at the firm level.

The results from the difference-in-differences analysis using the PPML estimator are shown in Table 8. The coefficients in columns (1) and (4) indicate no discernible increase in shipments or import volume from non-Chinese suppliers post-tariff implementation. In fact, the data in column (4) hint at a slight decline in the imports of the tariffed goods, even from these alternative sources. This finding could be attributed to the intricate and interconnected nature of global supply networks (Antràs and Chor, 2013). Tariffs imposed on Chinese goods may have had spillover effects, decreasing the demand for similar inputs from suppliers in other countries. Another possibility is that the relationships firms had with suppliers outside of China were not entirely independent, as they may have relied on intermediate goods originating from China, making it challenging for these

Table 8: Supply network reallocation under a persistent shock

This table presents results from stacked difference-in-differences Poisson pseudo-maximum likelihood (PPML) regressions of imports from countries other than China around the implementation of the 2018-2019 import tariffs. The sample is a firm-tariff wave-month panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. *Number of shipments from other countries* is the number of shipments of affected products from suppliers outside China. *Import volume from other countries* is the import volume in TEUs of affected products from suppliers outside China. *Treated* equals one for firms that imported from a supplier-product pair affected by the tariff increases in the year before the tariffs were implemented and zero otherwise. The *Post* indicator variable equals one in the post-tariff implementation period and zero otherwise. *HC* and *LL* are indicator variables that equal one if a firm had above median cash over assets or below median book leverage, respectively, in the year before a tariff wave was implemented. All specifications include fixed effects for firm×tariff wave and month×tariff wave. 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.

	Number of shipments from other countries			Import volume from other countries		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated×Post	0.014	0.013	−0.010	−0.118*	−0.106*	−0.131**
	(0.728)	(0.738)	(0.806)	(0.071)	(0.091)	(0.042)
Treated×Post×HC		−0.020			−0.054	
		(0.670)			(0.516)	
Treated×Post×LL			0.038			0.004
			(0.422)			(0.967)
Fixed effects						
Firm×wave	Yes	Yes	Yes	Yes	Yes	Yes
Month×wave	Yes	Yes	Yes	Yes	Yes	Yes
Observations	801,431	794,109	794,109	801,276	793,954	793,954
Pseudo R^2	0.26	0.26	0.26	0.32	0.32	0.32

suppliers to maintain their supply of the affected products in the face of tariffs.

The regression results presented in columns (2), (3), (5), and (6) of Table 8 explore the interaction between the treatment effect and firms' financial conditions before the tariff implementation. Specifically, these columns examine whether firms with higher liquidity (as indicated by above-median cash over assets) or lower financial leverage (as indicated by below-median book leverage) were more adept at shifting away from suppliers impacted by the tariffs. However, the interaction terms in these regressions yield statistically insignificant coefficients, suggesting that, on average, firms could not transition away from affected suppliers. Furthermore, these results imply that having greater financial resources did not significantly aid firms in substituting suppliers.

The findings from this analysis, rooted in a significant trade policy event, indicate that firms struggle to shift away from disrupted suppliers, even when the incentives to use pre-existing multi-sourcing relationships are substantial. This observation aligns with the idea that multi-sourcing may be less practical than some recent theoretical models suggest, especially when affected suppliers provide highly specialized goods. The evidence presented here also resonates with research indicating that the elasticity of substitution between suppliers is relatively low in the aftermath of shocks, particularly when the suppliers offer differentiated goods (e.g., Barrot and Sauvagnat, 2016; Khana, Morales, and Pandalai-Nayar, 2022).

6 Specialized inputs and bargaining dynamics

The preceding analysis establishes a robust positive relationship between supplier scarcity, input inventory levels, and book leverage and a strong negative relationship between supplier scarcity and cash holdings. By exploiting plausible exogenous variation in supply network fragility from the adoption of technologies that increase reliance on specialized inputs, the analyses also suggest these relationships are causal. However, there remains a concern that bargaining dynamics between suppliers and customer firms may confound the observed relationships. The issue is that supplier scarcity may not only be attributable to a limited number of suppliers for specialized inputs but also to contractual arrangements and firm-specific investments. This dual source of supplier scarcity presents two potential complications for the analysis. First, the actual fragility of supply networks might be understated if firm-specific investments in supplier relationships impede the ability of firms to switch suppliers, even when alternatives exist. Second, and perhaps more critically, the effects that have been attributed to the management of supply network risks might be a byproduct of the bargaining power dynamics inherent in supplier-customer relationships. If this is the case, the observed corporate policy adjustments may be responses to the bargaining environment rather than to supply network fragility per se. Importantly, this concern is not alleviated by exogenous variation in fragility from adopting new technologies since an increase in reliance on specialized inputs may exacerbate bargaining issues.

The "hold-up" problem is a classic illustration of the challenges that may arise when firms become vulnerable to suppliers who can leverage firm-specific investments to extract economic rents. This issue may compel firms to adopt the policy dynamics identified in my analysis as a defensive strategy against the potential exploitation by suppliers who gain market power through such investments (Klein, Crawford, and Alchian, 1978; Hart and Moore, 1988, 1990). The empirical literature provides evidence that supports this perspective. For instance, there is ample empirical evidence that firms adjust their corporate policies in response to a weakened bargaining position with their employees. For example, Bronars and Deere (1991) suggest that firms may increase their leverage to shield shareholders from the effects of unionization.

Similarly, DeAngelo and DeAngelo (1991) show that unionized firms might engage in earnings management, specifically by reporting lower profits, to negotiate more favorable terms with unions. Klasa, Maxwell, and Ortiz-Molina (2009) find that firms with unionized labor forces tend to maintain lower cash reserves. Collectively, these studies indicate that firms actively manage their financial policies in ways that reflect their bargaining positions with key stakeholders.

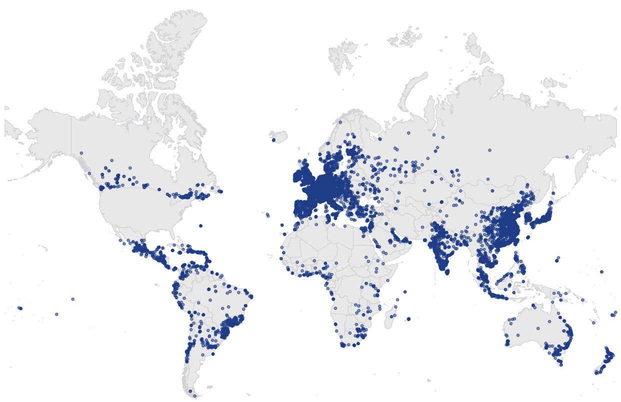
To disentangle the effects of supplier market power from those of supply network fragility, it is helpful to refer to Equation 24. In that equation, supply network fragility is comprised of two elements: the probability of disruptions within the supply network and the intrinsic attributes of the supply network that could exacerbate the effects of such disruptions on firms. This bifurcation suggests that managerial perceptions regarding the likelihood of future disruptions are a potential source of variation in supply network fragility independent of supply network and input characteristics and, consequently, the market power of suppliers.

Therefore, I examine the evolution of corporate policies around supply network disruptions that result from exogenous natural disasters, specifically floods, that occur at the locations of their suppliers. The data on these flood events is collected from the Dartmouth Flood Observatory at the University of Colorado, which compiles information from various sources such as media reports, governmental records, and satellite imagery. For each flood event, the dataset provides the event's beginning and end date, the geographical coordinates of its center, the total area affected in square miles, and a severity index that includes the number of casualties and displaced individuals. There are 2,122 flood events in the data since 2007.

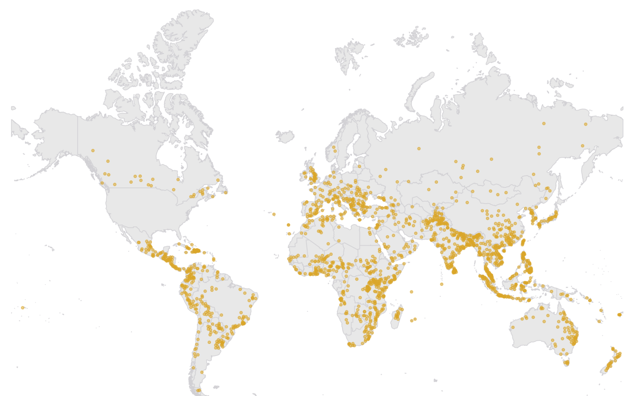
Figure 8 illustrates the geographic distribution of floods and the locations of affected suppliers, showcasing the substantial variation in the location of these natural disasters. In particular, the data

Figure 8: 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 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. Global supply network data are from ImportGenius and Panjiva.

Panel A: Geographic distribution of suppliers



Panel B: Geographic distribution of floods



are not limited to a specific region or time, which mitigates the risk that the floods may coincide with cyclical trade patterns or are restricted to certain areas. Among the significant events in the dataset are the March 2011 tsunami in Japan, triggered by the Tōhoku earthquake, and the Thailand floods of the same year. Both events had profound implications for U.S. manufacturers reliant on Japanese and Thai suppliers. The Tōhoku earthquake's tsunami is particularly notable for its disruption of the supply chains of American firms, as detailed in recent studies (e.g., Boehm, Flaaen, and Pandalai-Nayar, 2019). Similarly, the Thailand floods led to the closure of a critical Western Digital factory, which greatly impacted the computer manufacturing industry.[27]

As outlined at the beginning of this section, the empirical strategy is to utilize flood events as shocks to firms' subjective probabilities of future disruptions. For these tests, the critical point is not whether changes in subjective probabilities are consistent with objective probabilities or whether they reflect behavioral biases that make the probability of disruptions a more salient risk (Malmendier and Nagel, 2011; Bordalo, Gennaioli, and Shleifer, 2012, 2013). However, it is crucial to ensure that policy changes around these events are not merely ex-post responses to the floods. Given that the average flood event duration is only 11 days, persistent changes in corporate policies following these events are unlikely to be reactionary. The analysis, therefore, concentrates on the

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

evolution of corporate policies within five years surrounding these natural disasters.

6.1 Cross-sectional tests

The analysis of the impact of natural disasters on corporate policies begins by identifying suppliers affected by the floods. Specifically, I deem a supplier affected by a flood if the great-circle distance from the supplier to the flood's epicenter falls within the impacted area. The empirical models estimated are similar to Equation 25 but incorporate indicators that flag whether a firm's supplier has been affected by a flood within the preceding five years. Panel A of Table 9 presents the results. Column (1) shows a negative correlation between a flood event at a supplier's location and firms' cash holdings, with this effect intensifying over time. Column (3) demonstrates that firms exposed to a flood shock through their suppliers tend to maintain higher input inventories over assets, suggesting a strategic buffer against future supply disruptions. However, the relationship between supplier floods and firms' book leverage, although positive, does not show consistent statistical significance, as shown in column (2).

In Panel B of Table 9, the analysis focuses on the impact of floods on firms that rely on scarce suppliers, defined as those in the top quartile of a scarcity measure previously defined in Section 3.3. The results indicate that the persistent changes in corporate policies around flood events are greater when the supplier compromised by a flood is a scarce source of inputs. In addition to the effect on cash and inventory holdings, the results also show a positive relation between supplier disruptions and firm leverage.

The fact that floods are typically short-duration events but have lasting effects on corporate policies suggests that experiencing supplier disruptions due to natural disasters increases managers' subjective assessment of the likelihood of future disruptions. This shift in perception may prompt firms to adjust their policies accordingly, holding more cash and inventory and potentially increasing leverage as the risk of supply network fragility increases. These adjustments are consistent with the theoretical framework presented in Section 2, which posits that managers will alter their policies in anticipation of future risks to the supply network. The empirical evidence thus supports the model's predictions, indicating that managers are responsive to changes in the perceived probability

Table 9: Corporate policies and natural disasters
This table reports results from regressions of U.S. manufacturing firms' corporate policies around natural disasters. The sample is a firm-year panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. In Panel A, the *Flood* indicator variables equal one if a firm was exposed to a flood event through its suppliers in years $t-4$ to t and zero otherwise. In Panel B, the *Flood* indicator variables equal one if a firm was exposed to a flood event through one of its scarce suppliers, defined as a supplier in the upper quartile of the *Supplier scarcity* measure, in years $t-4$ to t and zero otherwise. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. All specifications include fixed effects for two-digit SIC industries and years. 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.

Panel A: All floods			
	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)
Flood_t	0.005^{**}	-0.009^{**}	0.002
	(2.121)	(2.467)	(0.356)
Flood_{t-1}	0.002	-0.007^{**}	0.002
	(1.054)	(2.165)	(0.505)
Flood_{t-2}	0.004^{*}	-0.013^{***}	0.008^{*}
	(1.676)	(3.728)	(1.824)
Flood_{t-3}	0.004^{**}	-0.008^{**}	0.005
	(2.184)	(2.452)	(1.045)
Flood_{t-4}	0.006^{**}	-0.013^{***}	0.005
	(2.534)	(3.799)	(1.050)
Controls	Yes	Yes	Yes
Fixed effects			
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	6,314	6,314	6,314
Adj. R^2	0.28	0.15	0.22

of supply network disruptions and adjust their firm's policies to mitigate the risks associated with supply network fragility.

6.2 Difference-in-differences estimations

The Propositions discussed in Section 2 have precise predictions about how corporate policies should dynamically change in response to supply network fragility. The flood events provide a useful natural experiment to examine if corporate policies change dynamically within firms to this source of risk as predicted by the model. Therefore, I refine the estimation of how natural disasters influence firm behavior by using a difference-in-differences methodology, paralleling the stacked

Table 9: Corporate policies and natural disasters (continued)

This table reports results from regressions of U.S. manufacturing firms' corporate policies around natural disasters. The sample is a firm-year panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. In Panel A, the *Flood* indicator variables equal one if a firm was exposed to a flood event through its suppliers in years $t-4$ to t and zero otherwise. In Panel B, the *Flood* indicator variables equal one if a firm was exposed to a flood event through one of its scarce suppliers, defined as a supplier in the upper quartile of the *Supplier scarcity* measure, in years $t-4$ to t and zero otherwise. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. All specifications include fixed effects for two-digit SIC industries and years. 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.

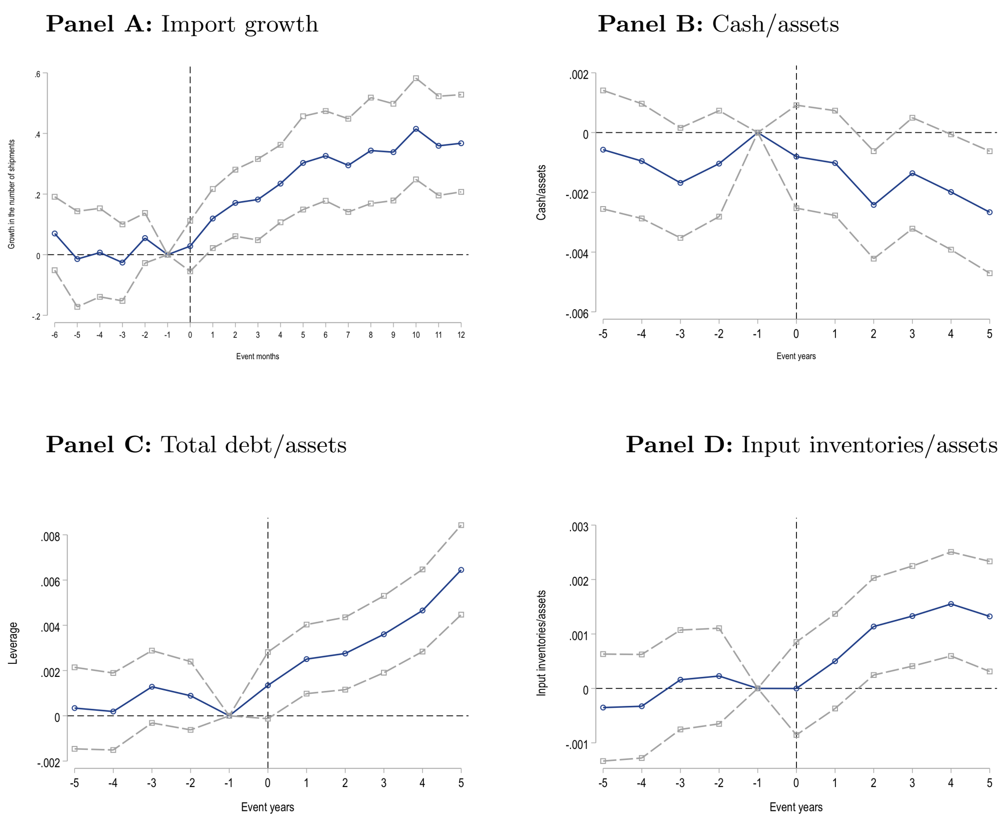
Panel B: Floods at scarce suppliers			
	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)
Flood_t	0.016^{**}	-0.012^{*}	0.023^{*}
	(2.094)	(1.850)	(1.782)
Flood_{t-1}	0.018^{***}	-0.013^{**}	0.024^{**}
	(2.610)	(2.224)	(1.970)
Flood_{t-2}	0.012^{*}	-0.013^{**}	0.023^{**}
	(1.691)	(1.971)	(2.001)
Flood_{t-3}	0.003	-0.008	0.024^{**}
	(0.381)	(1.308)	(2.074)
Flood_{t-4}	0.006	-0.017^{***}	0.014
	(0.757)	(2.648)	(1.282)
Controls	Yes	Yes	Yes
Fixed effects			
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	6,314	6,314	6,314
Adj. R^2	0.28	0.14	0.22

regression technique used in Section Section 5.2. In this setting, the stacked dataset comprises firms affected by a flood event (treated) and those not currently experiencing such an event (control). Additionally, because any particular natural disaster may impact a small set of firms, I ensure that treated and control firms are balanced 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 lagged log of assets and aggregate imports. Effectively, this matching ensures that the treated and control groups are comparable within their industry and have similar scale and importing behaviors before a natural disaster.

In the analysis, I estimate various models based on Equation 26 on the matched sample. The

Figure 9: Import growth and corporate policies around flood events

Panel A of this figure shows the estimated β coefficients (dark blue line) and 95% confidence intervals (light gray lines) from the following regression: $Import\ growth_{it} = \alpha_{ij} + \alpha_{tj} + \beta_0^j \sum_{t=-6}^{12} Event\ month_t^j + \beta_1^j \sum_{t=-6}^{12} Treated_i^j \times Event\ month_t^j + \epsilon_{it}$, where i indexes firms, j flood events, and t months. Similarly, Panels B, C, and D show the estimated β coefficients (dark blue line) and 95% confidence intervals (light gray lines) from the following regressions: $Y_{it} = \alpha_{ij} + \alpha_{tj} + \beta_0^j \sum_{t=-5}^{5} Event\ year_t^j + \beta_1^j \sum_{t=-5}^{5} Treated_i^j \times Event\ year_t^j + \epsilon_{it}$, where $Y_{i,t}$ is cash/assets, total debt/assets, or input inventories/assets. The β_1^j coefficients capture the average treatment effects in the corresponding time period around shock j. $Import\ growth_{it}$ is the year-over-year growth in the number of shipments. $Treated_i^j$ is an indicator variable that equals one if firm i is treated in flood event j and zero otherwise. $Event\ month_t^j$ is a vector of event month indicator variables. $Event\ year_t^j$ is a vector of event year indicator variables. α_{ij} and α_{tj} denote firm×flood event and time×flood event fixed effects, respectively. The dashed vertical line represents the start of the post-treatment period. Standard errors are clustered at the firm level.



dependent variables include the ratio of cash to assets, book leverage, the ratio of input inventories to assets, and the number of imports. I also include firm×flood event and time×flood event fixed effects to estimate average treatment effects across flood events and cluster standard errors at the firm level. This empirical strategy is similar to that of Barrot and Sauvagnat (2016) and Boehm, Flaaen, and Pandalai-Nayar (2019). However, instead of examining the immediate effects of the natural disaster shocks at supplier locations on firm output, my analysis focuses on more persistent changes in corporate policies and imports following these shocks.

For imports, I exploit the granularity of the BoL data to estimate a version of Equation 26 within a time frame spanning six months before and twelve months after the shocks. Panel A of Figure 9 presents the dynamic treatment effects estimates. The figure illustrates that the year-over-year growth in monthly shipments from affected suppliers increases markedly after a natural disaster at a supplier location. Notably, this growth in shipments reaches its peak at a 41% increase in the tenth month after the disaster event.

Next, I turn to the within-firm impact of the shocks on firms' input inventory holdings, cash reserves, and debt levels. I investigate how these corporate policies evolve in the five years around the shock by estimating specifications like that in Figure 9 but using a firm-year panel to match the frequency of the financial data. The results are presented in Table 10. The coefficients in column (1) suggest that the cash holdings of treated firms decrease by 2.5% relative to its pre-treatment mean compared to control firms in the five years following a natural disaster at a supplier location. However, the estimated treatment effect is only marginally statistically significant.

In contrast, the estimated treatment effects in columns (2) and (3) are more pronounced and statistically robust, suggesting that, on average, book leverage and inventory holdings increase by 60 and 10 basis points annually over the subsequent five years after a flood. To contextualize these effects, this equates to an average increase of 4.2% in book leverage and a 7.1% rise in inventory holdings relative to their pre-shock levels. Since firm leverage increases proportionately to the difference between input inventories and cash holdings, these findings support the theoretical predictions regarding firm leverage outlined at the end of Section 2.

The event study graphs in Panels B, C, and D of Figure 9, which correspond to the regressions in columns (1), (2), and (3) of Table 10, provide a visual representation of the difference-in-differences analysis. In these regressions, the variable *Treated* is interacted with indicators for each year from five years before to five years after the event, with the year of the event itself omitted. These graphs illustrate that, before the treatment, the differences in corporate policies between treated and control firms are negligible and not statistically significant. This observation supports the

Table 10: Within-firm changes in corporate policies around flood events

This table presents results from staggered difference-in-differences regressions of firm corporate policies around flood events. The sample is a firm-flood event-year panel of 895 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. *Treated* equals one for firms that imported from a supplier affected by a flood the year before the flood event and zero otherwise. All specifications include firm×flood and year×flood fixed effects. 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.

	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)
Treated × Post	0.001**	−0.001*	0.006***
	(2.116)	(1.753)	(4.967)
Fixed effects			
Firm × flood event	Yes	Yes	Yes
Year × flood event	Yes	Yes	Yes
Observations	322,145	321,725	322,145
Adj. R^2	0.89	0.73	0.81

parallel pre-trends assumption. Overall, the difference-in-differences results are consistent with the results in Section 6.1, reinforcing the conclusions drawn from the analysis.

7 Conclusion

Supply networks have become increasingly complex and global, offering economic benefits such as cost reductions and productivity gains. However, these global supply networks also introduce significant risks, particularly when firms are sensitive to supplier disruptions.

My research highlights reliance on specialized inputs and the scarcity of their suppliers as key contributors to the fragility of supply networks affecting U.S. manufacturing firms. To demonstrate the impact of this fragility on corporate strategies, I incorporate supply network fragility in a dynamic investment model with financing frictions. The model reveals that specialized input inventories are an effective hedge against supply network fragility, especially when firms cannot acquire specialized inputs from spot markets following disruptions. By increasing the buffer stock of input inventories, firms can ensure the continuity of production and cash flow generation during disruptions. In contrast, while cash holdings help mitigate the impact of disruptions ex-post, they do not help hedge the risk of supply network fragility ex-ante. Consequently, as supply network fragility intensifies, the optimal level of cash reserves decreases while the optimal level of inventories increases.

Additionally, as the likelihood of disruptions in specialized inputs rises, the marginal benefit of holding inventories over cash grows non-linearly. Consequently, firms might resort to debt financing when the expansion in inventory holdings exceeds the reduction in cash reserves. Therefore, firms with fragile supply networks substitute operating hedging for financial hedging by increasing input inventories at the expense of lower financial flexibility.

Leveraging novel data on the global supply networks of U.S. manufacturing firms, I empirically show that supply network fragility has a significant impact on corporate policies. In line with the theoretical model, firms with more fragile supply networks are characterized by higher levels of input inventories, lower cash-to-asset ratios, and higher book leverage. Moreover, plausibly exogenous variation in supply network fragility stemming from technology adoption and supply network disruptions suggests a causal interpretation of the findings.

The implications of my study extend beyond the immediate effects of the transmission of supplier shocks on customer firms. In particular, my findings show the ex-ante steps firms take to increase their production resilience, particularly when potential disruptions could hinder their access to specialized inputs essential for production.

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Appendix A: Variable definitions

Variable	Definition
Asset growth	Year-on-year asset growth.
Cash/assets	Cash and marketable securities over assets.
Cash flow/assets	EBITDA minus interest, taxes, and common dividends over assets.
Capex/assets	Capital expenditures over assets.
COGS/assets	Cost of goods sold over assets.
Foreign supplier (%)	The proportion of a firm's foreign suppliers derived from Compustat segments data.
Innovation	R&D expenditures divided by lagged assets.
Input complexity	One minus the sum of square import volume shares across import product HS codes in a year.
Input inventories/assets	Materials and supplies for use in production and in-process goods not ready for sale over assets.
Intermediate inputs import share	Share of import volume comprised of intermediate inputs.
Investment	Capital expenditures divided by lagged gross property, plant, and equipment.
Market-to-book ratio	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 leverage	The natural log of total assets.
R&D/sales	Research and development expenditures over sales.
(Rental expenses/assets)×100	Rental expenses over assets multiplied by 100.

Variable	Definition
Specialized components import share	Share of import volume comprised of specialized electronic components and scarce raw materials.
Supplier scarcity	The additive inverse of the import volume-weighted average number of alternative suppliers across import products HS codes in a year.
Total debt/assets	Book leverage measured as long-term debt plus debt in current liabilities over assets.
Technology adoption$_{[1986,1995]}$	The average frequency of terms related to emerging technologies in firms' MD&A section of their 10-K financial reports from 1986 to 1995.

Appendix B: Derivations and proofs

The Lagrangian function for the period $t+1$ maximization problem in Equation 2 can be written as follows:

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

where,

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

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

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

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

and μ_{t+1} and η_{t+1} are the Lagrange multipliers on the constraints in Equation 3 and Equation 4, respectively. The optimal decisions on $P_{g,t+1}, P_{s,t+1}, B_{t+1}$, and the debt constraints satisfy the following first-order conditions:

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

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

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

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

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

In period t, the firm solves the problem in Equation 14. The Lagrangian function associated with that problem can be written as:

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

where,

$$N_{g,t} = P_{g,t} - i_{g,t}$$

$$N_{s,t} = P_{s,t} - i_{s,t}$$

where μ_t, η_t, $\delta_{g,t}$, $\delta_{s,t}$, and γ_t are the Lagrange multipliers on the constraints in Equation 15 and Equation 16. The optimal decisions on $P_{g,t}, P_{s,t}, i_{g,t}, i_{s,t}, C_t, B_t$, and the debt constraints satisfy the following first-order conditions:

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

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

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

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

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

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

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

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

where,

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

and

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

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. These marginal costs encompass both the costs of issuing debt in period t and the shadow value of the debt capacity constraint. Analogously, 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 includes savings on financing costs when the firm faces resource constraints in period $t+1$, the real net marginal gain in expected cash flows from alleviating such constraints, and the residual value of inventories and cash when the firm is not resource constrained.

B.1 Benchmark

Proof of Proposition 1: First note that when $\rho_s = 0$, $\delta_{g,t} = \delta_{s,t}$. Thus, without loss of generality, consider Equation B12 and Equation B13. By subtracting Equation B12 from Equation B13, we obtain:

$$\delta_{s,t} = \mathbb{E}_t \alpha \psi + \gamma_t > 0$$

Since $\delta_{s,t} = \delta_{g,t} > 0$, the non-negativity constraints on $i_{g,t}$ and $i_{s,t}$ bind. Therefore, $i^*_{g,t} = i^*_{s,t} = 0$. The second result follows from the assumption in the proposition. To see this, suppose that $\gamma_t > 0$. Then, $F(z_{t+1}, N_{g,t+1}^{\hat{}}, N_{s,t+1}^{\hat{}}) > F(z_{t+1}, N^*_{g,t+1}, N^*_{s,t+1})$, which is a contradiction. Therefore, $\gamma_t = 0$ and $C^*_t > 0$.

B.2 Ex-ante supply network fragility

Proof of Proposition 2: $i^*_{g,t} = 0$ by Proposition 1. Thus, first consider the effect of an increase in ρ_s on the marginal benefit of cash holdings in the left side of Equation B13. Using the Leibniz integral rule, this is given by:

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

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

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

Therefore,

$$\frac{\partial MB_{i_{s,t}}}{\partial \rho_s} - \frac{\partial MB_{C_t}}{\partial \rho_s} = \frac{1-\alpha}{(1-\rho_s)^2}\mathbb{E}_t\psi > 0$$

since $\alpha \in (0,1)$ and $\rho_s \in (0,1)$. Hence, since the marginal benefit of inventory holdings increases relative to cash holdings, $\frac{\partial C^*_t}{\partial \rho_s} < 0$ and $\frac{\partial i^*_{s,t}}{\partial \rho_s} > 0$, *ceteris paribus*.

Appendix C: Data

This section presents additional details on the construction of the global supply network data, stylized facts, and further analyses to affirm the quality of the global supply network data and the supplier scarcity measure of supply network fragility.

C.1 Bill of lading form example

Figure C1 shows an example of a BoL form. As seen in the example, the BoL form collects detailed information on the vessel used to transport the goods, the consignee (i.e., recipient), and the supplier, as well as import product descriptions and quantity information such as the weight and volume of the imported goods occupy in the vessel.

C.2 Supplier identifiers

This section outlines the methodology for distinguishing unique suppliers in the BoL data. Initially, supplier names are standardized by removing punctuation marks such as periods, commas, hyphens, and apostrophes and converting all text to lowercase for uniformity. Subsequently, a vectorial decomposition algorithm is applied to compare supplier names. This algorithm utilizes bigram matching, which are pairs of consecutive words within the names. The inherent strength of bigram vectorial decomposition and n-gram techniques, more broadly, lies in their robustness to typographical errors. These methods preserve local context despite misspellings by focusing on pairs of adjacent characters or words. For instance, a misspelled word like "hte" still retains bigrams "ht" and "te," which are similar to the correct bigrams "th" and "he" in "the." This feature is particularly advantageous given that the most frequent cause for discrepancies in supplier names within the data is minor misspellings in the BoL documents.

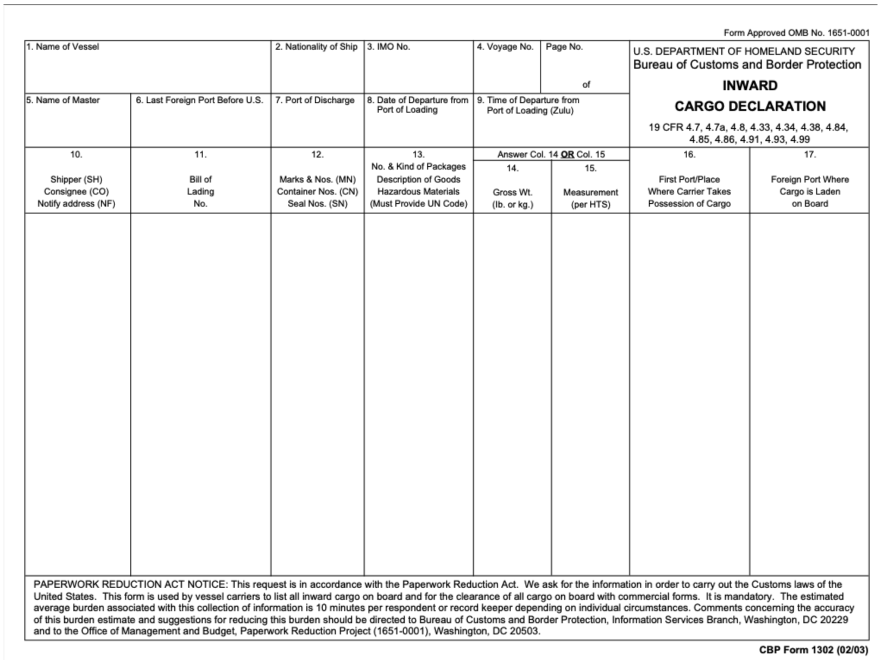
The algorithm calculates a similarity score between two supplier name strings using the following formula:

$$Similarity = \frac{2 \times m}{s_1 + s_1} \tag{C1}$$

where s_1 and s_2 represent the total number of bigrams in strings one and two, respectively, and m

Figure C1: 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

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CBP Form 1302 (02/03)

is the total number of bigrams matched between the two strings. This formula yields a similarity score between zero and one, with higher numbers indicating higher similarity between the two strings. To be identified as the same supplier, two names must have a similarity score of at least 80%, indicating that at least 80% of the bigrams in the two strings are the same. This stringent cut-off ensures high confidence in the matches. However, I also confirmed the quality of the matches by manually comparing the matched supplier names in a random sample of 300 suppliers.

C.3 Stylized facts

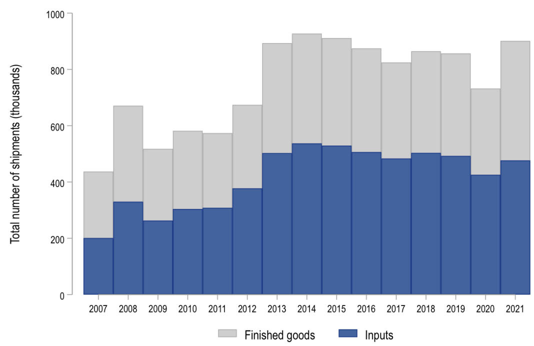
In this section, I present several styled facts about the global supply networks of sample U.S. manufacturing firms. First, I examine the evolution of aggregate imports and establish that, throughout the sample period, most of these imports are of input materials. Secondly, I explore the geographical distribution of suppliers and the structure of the network that connects inputs to suppliers. Despite the extensive global reach of these networks, I find that imports are heavily concentrated in a few countries, and the connections between suppliers and specific inputs are often limited.

Figure C2 presents data on the total number of shipments (Panel A) and the total volume of

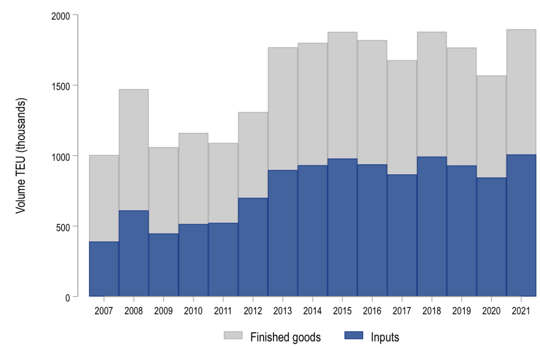
Figure C2: Annual import activity

This figure shows the total number of shipments (Panel A) and import volume in twenty-foot equivalent units (Panel B, TEUs) sourced by firms from 2007 to 2021. In each panel, the bars' light (dark) portion depicts the number of shipments or import volume accounted for by finished (input) goods. Imports are classified into inputs (raw materials and intermediate goods) or finished goods using World Bank Harmonized System (HS) code definitions. The sample comprises 895 publicly listed U.S. manufacturing firms with global supply networks. Global supply network data are from ImportGenius and Panjiva.

Panel A: Number of shipments



Panel B: Import volume (TEUs)



imports measured in TEUs (Panel B). Since 2007, sample manufacturing firms have received over half a million shipments through maritime transport, translating to over a million TEUs. These figures peaked in 2014 and 2015, with firms receiving nearly 1 million shipments and 1.8 million TEUs. However, imports by manufacturing firms were significantly lower during downturns. For example, during the global financial crisis, there was a marked dip in the total number of shipments and the volume of imports. In 2020, these numbers fell by 23% and 28%, respectively.

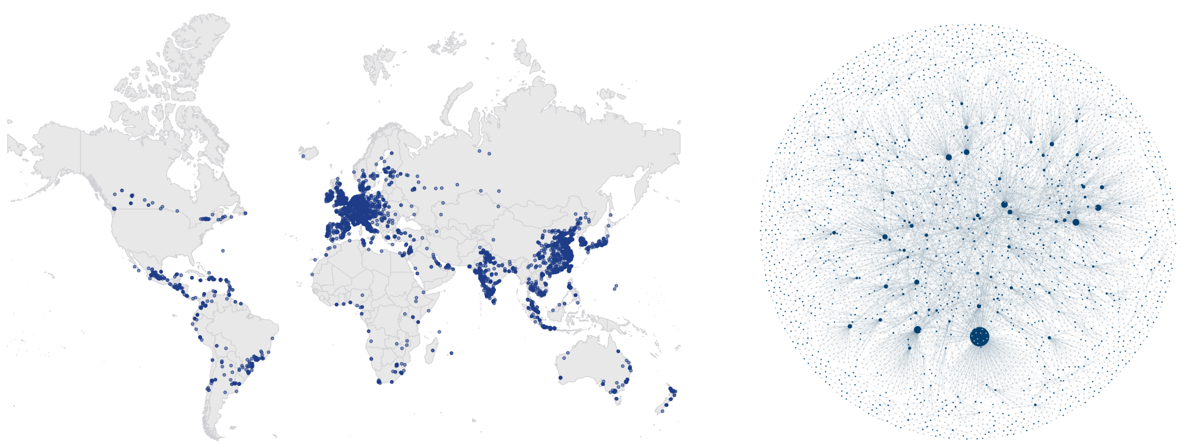
The figure also shows a decomposition of total imports by U.S. manufacturing firms into imports comprising raw materials and intermediate goods, collectively termed "inputs," and final goods. On average, inputs constitute 55% of the imports by these firms during the sample period, with the remaining 45% being finished products. This indicates that for the firms in the sample, the bulk of imports from foreign suppliers consists of inputs. These trends align with the growing prominence of specialized intermediate inputs over final goods in international trade (Antràs and Staiger, 2012).

Panel A of Figure C3 maps out the geographic distribution of foreign suppliers for U.S. manufacturing firms as of 2021. This depiction confirms the extensive foreign supplier network, with U.S. manufacturing firms procuring inputs and finished goods from over 11,000 foreign suppliers across 136 countries. Yet, suppliers are not evenly distributed across countries. For instance, in 2021,

Figure C3: The geographic distribution and network linkages of suppliers
Panel A of this figure shows the geographic distribution of foreign suppliers of sample firms in 2021. Panel B depicts the network structure of inputs and their suppliers from 2007 to 2021. Each blue node represents a unique input Harmonized System (HS) code, and each gray dot represents an individual supplier. The edges between the nodes represent the sourcing availability of each input from different suppliers. The sample comprises 895 publicly listed U.S. manufacturing firms with global supply networks. Global supply network data are from ImportGenius and Panjiva.

Panel A: Geographic distribution of suppliers

Panel B: Input-supplier network



31% of the foreign suppliers listed in the BoL data were based in China. Moreover, the network of input-supplier connections is characterized by considerable variability. Panel B of Figure C3 illustrates this network and indicates that many inputs are sourced from a limited number of suppliers worldwide. In some extreme cases, certain inputs are sourced exclusively from a single supplier, as depicted by the node pairs on the periphery of the graph. These patterns are consistent with the scarcity of suppliers for specific inputs documented in Section 3.3.

C.4 Data validation

Section 3.2 illustrates that maritime shipments accounted for most imports in 2021. This section shows that these patterns extend to the time series since the early 2000s and that there are no material systematic differences in the mode of transportation used for imports across the set of industries and HS codes spanned by sample manufacturing firms. For instance, Panel A of Figure C4 demonstrates that, in terms of import value, maritime shipments have consistently represented the bulk of aggregate imports from 2003 to 2021. The preeminence of maritime imports over other

Figure C4: Evolution of imports by mode of transportation
This figure shows the time series of aggregate imports by mode of transportation (Water, Air, and Other). The "Other" category includes pipeline, truck, and rail imports. In Panels A and B, imports are measured in dollar values and weight, respectively. In Panel A, the time series is from 2003 to 2021. In Panel B, it is from 2009 to 2021. These data are from the U.S. Census Bureau.

Panel A: Import value **Panel B:** Import weight

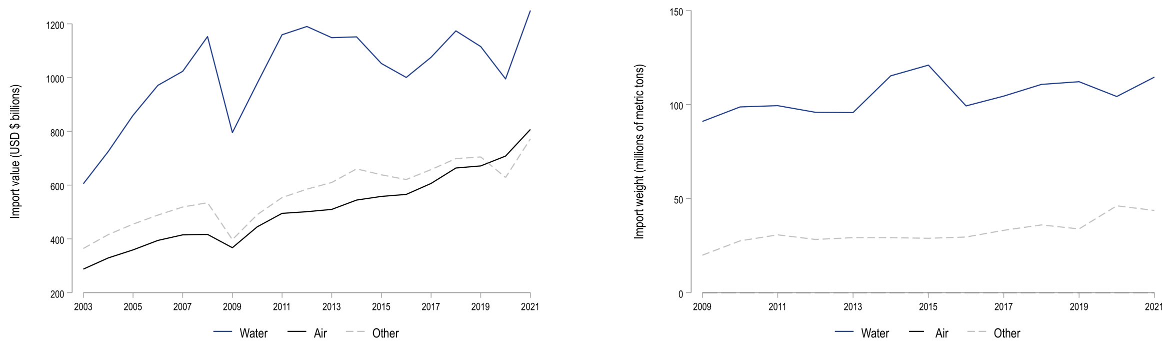
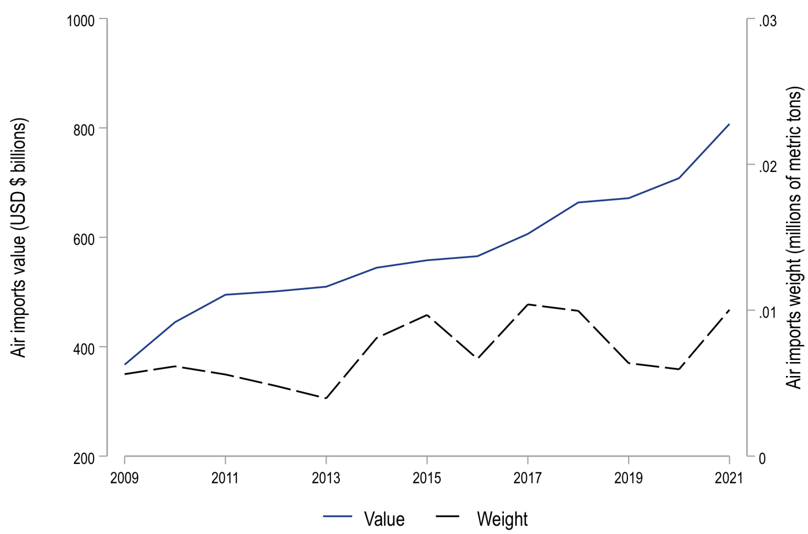


Figure C5: Evolution of air imports
This figure shows the evolution of air imports in terms of dollar values (left axis) and import weight (right axis) from 2009 to 2021. These data are from the U.S. Census Bureau.



transportation modes becomes even more apparent when considering the dollar value of imports, as shown in Panel B, where maritime imports significantly surpass those of any other mode from 2009 to 2021.[28]

[28] Note that the time-series of imports by mode of transportation in millions of metric tons begins in 2009. Additionally, the average weight of air imports during this period is a mere 0.007 million metric tons.

It is worth noting that the role of air imports grew in comparison to maritime shipments during the COVID-19 pandemic due to shipping delays, capacity constraints, and rising transportation costs.[29] This shift is reflected in the surge of aggregate air imports in both value (left-axis) and weight (right-axis) during 2020 and 2021, as depicted in Figure C5.[30]

I also examine how the aggregate value of maritime and air imports differs across HS product codes. I focus on the top ten HS codes, ranked by the dollar value of aggregate imports for both maritime and air transport. Panels A and B in Figure C6 depict the annual percentage of imports attributed to each HS code from 2009 to 2021 for maritime and air imports, respectively.[31]

The composition of the top ten HS codes for maritime and air imports reveals distinct patterns in product transportation preferences. For instance, mineral fuels, which on average account for 26% of maritime imports among the top ten HS codes, are notably absent from the top ten HS codes for air imports. Conversely, pharmaceuticals hold a substantial share of air imports within the top ten HS codes annually, yet they do not feature among the top ten for maritime imports.

However, the substantial overlap in specialized products between maritime and air imports is noteworthy. Specifically, electrical components and machinery make up 31% of maritime imports among the top ten HS codes. Concerning air imports, these categories, along with optical instruments—which encompass similar items to those under electrical components—represent 33% of the top ten HS codes. Therefore, due to the observed similarities, it is unlikely that assessments of supply network fragility based on maritime imports would systematically overlook specific dimensions of fragility related to the characteristics of inputs, decreasing concerns of non-classical measurement error.

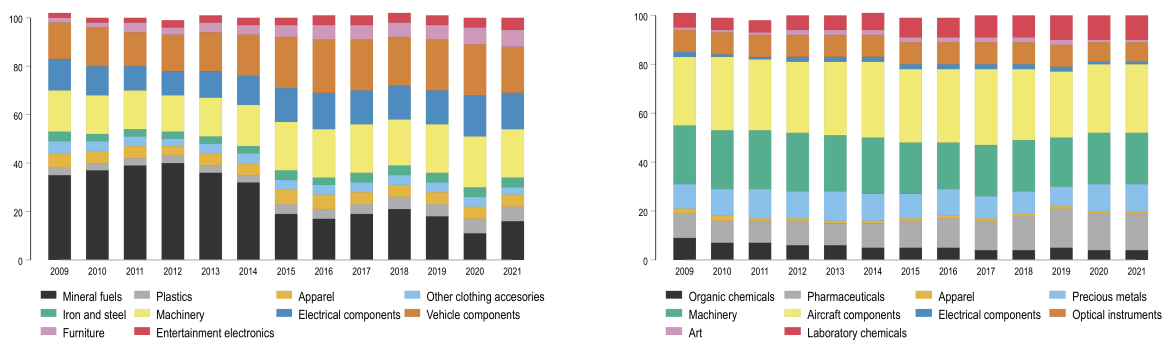
[29] See "I've never seen anything like this': Chaos strikes global shipping," by Peter S. Goodman, Alexandra Stevenson, Niraj Chokshi, and Michael Corkery, March 6, 2021, *The Wall Street Journal*.

[30] Given the high persistence of the supplier scarcity measure of supply network fragility, as evidenced in Figure 5, the empirical results are unlikely to be significantly impacted by the temporary shift from maritime to air transport in 2020 and 2021. Nonetheless, Table D5 confirms that the core findings remain consistent even after excluding 2020 and 2021 from the analyses.

[31] The decomposition of imports across HS product categories began in 2009.

Figure C6: 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 2021. These data are from the U.S. Census Bureau.

Panel A: Maritime imports **Panel B:** Air imports



C.5 Validation of the supplier scarcity measure

To validate the supplier scarcity measure defined in Section 3.3, I first provide illustrative cases for ten companies with the most fragile supply networks as indicated by the supplier scarcity measure. Table C1 lists these companies, specifying their industry and summarizing the nature of their products. The first company on the list describes itself on its website as follows: "One Stop Systems, Inc. (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 Ion Accelerator™ SAN, NAS and data recording software. These products are used for AI data set capture, training, and large-scale inference in the defense, oil and gas, mining, autonomous vehicles and rugged entertainment applications." This profile strongly suggests a dependency on specialized inputs for product manufacturing. Notably, OSS explicitly acknowledges supply chain risks in the "Nature of Operations" section of its most recent 10-Q financial report, highlighting that such risks could constrain its ability to attract customers and innovate.

The remaining listed companies also manufacture highly specialized products, likely necessitating specialized inputs. For instance, the group includes firms engaged in producing sophisticated communication devices, as well as healthcare companies dedicated to manufacturing unique diag-

Table C1: Top ten firms by supplier scarcity

This table lists the ten firms with the most fragile supply networks according to the supplier scarcity measure. To rank the firms, I computed the within-firm average of the supplier scarcity measure from 2007 to 2021 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-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021.

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

nostic instruments and surgical devices. In addition to companies dependent on specialized inputs for production, one notable firm on the list, Yeti Holdings, focuses on creating vacuum-insulated stainless-steel drinkware and coolers, among other items. While its inclusion may initially seem surprising, Yeti Holdings explicitly acknowledges in its financial disclosures the procurement challenges it encounters for critical raw materials such as Polyethylene, Polyurethane foam, Polyester fabric, and various plastic components from its suppliers.

To examine the link between the supplier scarcity measure and supply network risk more rigorously, I adopt a textual analysis methodology similar to that used by Hassan et al. (2019). Specifically, this approach involves identifying discussions of supply network risk within firms' 10-K financial reports by differentiating textual patterns indicative of supply network risk from those that are not. Following the method of Hassan et al. (2019), I use the tenth edition of the textbook on financial accounting by Libby, Libby, and Hodge (2019) as a corpus of text unrelated to supply network risk, but that is representative of the textual information in financial disclosures. Conversely, I use The White House (2021) report on building resilient supply chains as the training corpus of text that is related to supply network risk.

The texts from the White House supply chain report and financial accounting textbook are

Table C2: Textual measures of supply network risk and supplier scarcity

This table reports results from regressions of textual measures of supply network risk on supplier scarcity, an ex-ante measure of supply network fragility. The sample is a firm-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. The textual measure of supply network risk is constructed using a bigram approach in columns (1) and (2) and a cosine similarity approach in columns (3) and (4). Under 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). Under 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.

	Textual measures of supply network risk			
	Bigrams		Cosine similarity	
	(1)	(2)	(3)	(4)
Supplier scarcity	0.008**	0.006**	2.108***	1.856***
	(2.097)	(2.046)	(8.984)	(8.045)
Fixed effects				
Industry	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes
Observations	9,974	9,974	9,974	9,974
Adj. R^2	0.30	0.31	0.70	0.70

converted into bigrams, and the occurrences of each bigram are counted. When processing each 10-K document, the text is similarly broken down into bigrams. The occurrences of these bigrams within a ten-word radius of keywords such as "risk" and "uncertainty" are counted. A score is then computed reflecting the differential in bigram occurrences between the 10-K reports and the reference texts, normalized by the total bigram count in the 10-K documents. This method quantifies the contextual relationship between terms relevant to supply network risk and the surrounding text, yielding a measure of supply network risk as articulated in the 10-K reports.

I implement an alternative textual measure of supply network risk, recognizing that firms may not consistently mention supply network concerns in conjunction with terms like "risk" and "uncertainty." This method involves comparing the cosine similarity between the bigram frequency vector from the White House report and those derived from firms' 10-K reports. The cosine similarity score, which ranges from zero to one, quantifies the likeness between two vectors, with zero indicating no overlap and one signifying identical bigram frequencies.

To determine whether the supplier scarcity measure outlined in Section 3.3 accurately reflects supply network risk as discussed in 10-K reports, I conduct regression analyses with the textual measures of supply network risk derived from the bigram and cosine similarity methods as dependent variables. The findings, presented in Table C2, reveal a robust positive correlation between the supplier scarcity measure and the frequency of supply network risk discussions in firms' financial disclosures. This positive correlation further substantiates the supplier scarcity measure as a credible indicator of supply network fragility.

Appendix D: Additional results and robustness tests

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

D.1 Supply network fragility, cost of goods sold, and rental expenses

As shown in Section 4, supply network fragility has a large effect on input inventory holdings. Given that inventory carrying costs can be substantial, up to 30% of inventory value (e.g., Ramey, 1989), and that various components of these costs appear as expenses on the income statement, it is plausible to anticipate that firms with fragile supply networks would incur higher operating costs. These costs may include storage, insurance, and depreciation, which may be reflected in COGS or as separate operating expenses.

To explore the connection between supply network fragility and operating costs, I examine the relationship between supplier scarcity, COGS, and rental expenses. The findings presented in Table D1 align with the findings of Section 4, showing a positive correlation between greater supplier scarcity and both COGS and rental expenses. This suggests that firms with more fragile supply networks, as indicated by higher supplier scarcity, tend to have elevated operating costs, likely due to increased expenses associated with maintaining larger inventory levels.

D.2 Controlling for the importance of domestic suppliers

One limitation of the available data on global supply networks is its omission of information regarding domestic suppliers, which may raise concerns about the completeness of the supply network fragility measures. To the best of my knowledge, no existing data provides detailed information on domestically sourced inputs for U.S. manufacturing firms, precluding the construction of the supplier scarcity measure accounting for domestic suppliers. Nevertheless, I address this limitation by analyzing the sensitivity of the results in Panel A of Table 2 to the relative importance of foreign supply networks at the firm level.

If the fragility measures based on global data do not fully capture the role of domestic suppliers, one might expect to see stronger effects for firms that rely more heavily on foreign suppliers. To

Table D1: Supply network fragility and operating costs

This table reports results from regressions of U.S. manufacturing firms' cost of goods sold (COGS) and rental expenses on supplier scarcity, an ex-ante measure of supply network fragility. The sample is a firm-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. 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.

	COGS/assets		(Rental expenses/assets)×100	
	(1)	(2)	(3)	(4)
Supplier scarcity$_{t-1}$	0.142***	0.103***	0.258**	0.117**
	(3.893)	(3.294)	(2.512)	(2.245)
Controls	Yes	Yes	Yes	Yes
Fixed effects				
Industry	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes
Observations	9,046	9,046	9,046	9,046
Adj. R^2	0.09	0.29	0.06	0.33

investigate this, I utilize Compustat segments data to determine the proportion of foreign suppliers for each firm, identified through their disclosures in 10-K financial reports.[32] I then create an interaction term between this proportion and the supplier scarcity measure and re-estimate the regressions from Panel A of Table 2 including the interaction terms.

The estimated coefficients on the standalone *Foreign suppliers (%)* variable are positive and significant in columns (1) and (2) and negative and significant in columns (3) and (4), indicating that firms with a higher proportion of foreign suppliers tend to have higher cash-to-asset ratios and less debt. These results are intuitive as firms with more foreign suppliers will likely be larger. However, none of the interaction terms are statistically significant, and the estimated coefficients on the supplier scarcity variable are nearly identical to those presented in Panel A of Table 2. The fact that the estimated coefficients remain largely invariant, regardless of the relative importance of domestic to foreign suppliers at the firm level, mitigates concerns that the supply network fragility measures may be biased due to the omission of domestic suppliers.

[32] In this dataset, foreign suppliers are limited to foreign entities cross-listed in the U.S.

D.3 Alternative supply network fragility measures

The robustness of the results in Panel A of Table 2 are further examined by considering alternative measures of supply network fragility that align with recent theoretical models and the model presented in Section 2. These alternative measures aim to capture the degree of reliance on specialized inputs, which is a key aspect of supply network fragility. The first alternative measure is the proportion of imports that are intermediate inputs. A higher proportion suggests a greater reliance on specialized inputs, potentially indicating a more fragile supply network. The second measure considers the proportion of imports of specialized electronic components and scarce raw materials. These categories of imports are often critical to production and tend to be concentrated in few suppliers (Miller, 2022). Thus, their proportion can serve as an indicator of fragility. The third measure is the complexity of the input mix used by firms. This measure is informed by the model of Elliott, Golub, and Leduc (2022), which posits that the complexity of a firm's input mix affects the functionality of its supply network, particularly in the face of supplier disruptions.

By testing the robustness of the main results against these alternative measures, the analysis seeks to ensure that the findings are not sensitive to the specific empirical proxy of supply network fragility used. If the results hold across different measures, it would strengthen the argument that supply network fragility is a significant determinant of firms' corporate policies.

I classify imports into intermediate inputs or specialized electronic components using HS codes. For intermediate inputs, I use World Bank classifications. For specialized electronic components, I use classifications by the U.S. Census Bureau and manual classifications following The White House (2021) report on building resilient supply chains.[33]

Table D3 shows results of estimations equivalent to those presented in Panel A of Table 2 but with the alternative measures of supply network fragility in place of supplier scarcity. For brevity, Table D3 shows results only for regressions with industry fixed effects, but results are similar if industry fixed effects are excluded. Panel A shows results for input inventories and Panel B for cash holdings and book leverage. The results indicate that regardless of the empirical measure of

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

supply network fragility used, the conclusions drawn from the results in Panel A of Table 2 still hold. Namely, supply network fragility is associated with higher holdings of input inventories, lower cash holdings, and higher book leverage.

Table D2: Controlling for the importance of domestic suppliers

This table reports results from regressions of U.S. manufacturing firms' financial policies and inventory holdings on supplier scarcity, an ex-ante measure of supply network fragility, and interactions with the proportion of foreign suppliers. The sample is a firm-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Supplier scarcity* is the additive inverse of the number of shipments-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. *Foreign suppliers (%)* is the proportion of a firm's foreign suppliers. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. 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.

	Input inventories/assets		Cash/assets		Total debt/assets	
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier scarcity$_{t-1}$	0.017***	0.018***	−0.079***	−0.072***	0.030***	0.024**
	(2.858)	(3.040)	(5.828)	(5.396)	(3.065)	(2.491)
Foreign suppliers (%)$_{t-1}$	−0.005	−0.007	0.050**	0.035*	−0.076***	−0.064***
	(0.717)	(1.091)	(2.061)	(1.762)	(4.664)	(4.557)
Supplier scarcity$_{t-1}$ × Foreign suppliers (%)$_{t-1}$	−0.010	0.011	0.056	0.056	−0.054*	−0.049
	(0.752)	(0.718)	(1.038)	(1.241)	(1.956)	(1.442)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Industry	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,046	9,046	9,046	9,046	9,046	9,046
Adj. R^2	0.13	0.24	0.12	0.18	0.16	0.21

Table D3: Alternative measures of supply network fragility

This table reports results from regressions of U.S. manufacturing firms' financial policies and inventory holdings on alternative ex-ante measures of supply network fragility. The sample is a firm-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Intermediate inputs import share* is the share of import volume comprised of intermediate inputs in a year. *Specialized components import share* is the share of import volume comprised of specialized electronic components and scarce raw materials in a year. Imports are classified into intermediate and specialized inputs using Harmonized System (HS) codes. I follow World Bank classifications for intermediate inputs and U.S. Census Bureau and manual classifications for specialized inputs. *Input complexity* is defined as one minus the sum of square import volume shares across import product HS codes in a year. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. 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.

Panel A: Input inventories			
	Input inventories/assets		
	(1)	(2)	(3)
Intermediate inputs import share$_{t-1}$	0.020***		
	(3.470)		
Specialized components import share$_{t-1}$		0.019***	
		(4.812)	
Input complexity$_{t-1}$			0.022***
			(8.408)
Controls	Yes	Yes	Yes
Fixed effects			
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	9,066	9,107	9,090
Adj. R^2	0.24	0.24	0.24

Panel B: Cash holdings and book leverage						
	Cash/assets	Total debt/assets	Cash/assets	Total debt/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediate inputs import share$_{t-1}$	-0.046^{***}	0.044^{**}				
	(3.672)	(2.381)				
Specialized components import share$_{t-1}$			-0.080^{***}	0.052^{***}		
			(4.383)	(2.791)		
Input complexity$_{t-1}$					-0.085^{***}	0.041^{**}
					(6.373)	(2.564)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,066	9,066	9,066	9,066	9,090	9,090
Adj. R^2	0.17	0.21	0.18	0.21	0.18	0.21

Finally, I examine the robustness of the findings in Panel A of Table 2 to the weighting methodology employed in the supplier scarcity measure. The focal measure uses weights proportional to import volume in TEUs, which could underweight inputs that occupy little space. Thus, I re-estimate the results in Panel A of Table 2 using an alternative supplier scarcity metric that assigns weights based on the number of shipments received for each input. The results in Table D4 uphold the initial findings. The relationship between supply network fragility, corporate financial policies, and input inventory levels remains consistent, irrespective of the weighting scheme applied to the supplier scarcity measure.

D.4 The COVID-19 pandemic period and year-specific shocks

At the onset of the COVID-19 pandemic, firms faced a combination of supply and demand shocks (Baqaee and Farhi, 2022). For instance, firms faced difficulties maintaining production because of supplier disruptions, social distancing rules, and concerns over employee health. Likewise, demand for certain products plummeted due to lockdown measures and shifts in consumer preferences. Furthermore, the pandemic underlined the value of financial flexibility, prompting firms to bolster their cash reserves, often through drawdowns on credit lines (Fahlenbrach, Rageth, and Stulz, 2020; Acharya and Steffen, 2020). To the extent that these dynamics were more pronounced for firms with ex-ante fragile supply networks, the findings I document could be an artifact of the COVID-19 pandemic period. To this end, I re-estimate the results presented in Panel A of Table 2, dropping years 2020 and 2021 from the analysis. The results in Panel A of Table D5 confirm that the COVID-19 crisis does not drive the documented relationship between supply network fragility and corporate policy decisions.

A related concern is that despite controlling for year-specific fixed effects that control for common shocks across all firms in a year, error terms may still be correlated within years. Even though the number of clusters in the year dimension is small (i.e., only 15 years), I estimate regressions equivalent to those in Panel A of Table 2 but where standard errors are clustered by both firm and year. The results presented in Panel B of Table D5 show that inferences drawn from Panel A of Table 2 are unchanged.

Table D4: Weights proportional shipment counts

This table reports results from regressions of U.S. manufacturing firms' financial policies and inventory holdings on supplier scarcity, an ex-ante measure of supply network fragility. The sample is a firm-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Supplier scarcity* is the additive inverse of the number of shipments-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. 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.

	Input inventories/assets		Cash/assets		Total debt/assets	
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier scarcity$_{t-1}$	0.016^{**}	0.017^{***}	-0.080^{***}	-0.073^{***}	0.027^{***}	0.022^{**}
	(2.581)	(2.849)	(5.816)	(5.469)	(2.779)	(2.231)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Industry	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,090	9,090	9,090	9,090	9,090	9,090
Adj. R^2	0.13	0.24	0.12	0.18	0.16	0.21

D.5 Additional instrumental variables results

This subsection presents robustness tests on the IV estimates presented in Section 5.1. In particular, Table D6 shows that the results in Panels A and B of Table 4 are similar when the models are estimated without industry fixed effects.

Table D5: Excluding the COVID-19 pandemic period and year-specific shocks

This table reports results from regressions of U.S. manufacturing firms' financial policies and inventory holdings on supplier scarcity, an ex-ante measure of supply network fragility. The sample is a firm-year panel of 895 U.S. manufacturing firms with global supply networks from 2007 to 2021. *Supplier scarcity* is the additive inverse of the number of shipments-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. In Panel A, the years 2020 and 2021 are excluded from the estimation sample, and t-statistics based on standard errors clustered at the firm level are reported in parentheses below coefficient estimates. In Panel B, t-statistics based on standard errors clustered at the firm and year 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.

Panel A: Excluding the COVID-19 pandemic period

	Input inventories/assets		Cash/assets		Total debt/assets	
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier scarcity$_{t-1}$	0.017***	0.018***	-0.077^{***}	-0.069^{***}	0.036**	0.030***
	(2.732)	(2.908)	(5.400)	(4.960)	(2.439)	(3.056)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Industry	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,751	7,751	7,751	7,751	7,751	7,751
Adj. R^2	0.13	0.23	0.10	0.17	0.15	0.21

Panel B: Double clustering by firm and year

	Input inventories/assets		Cash/assets		Total debt/assets	
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier scarcity$_{t-1}$	0.017**	0.018***	-0.079^{***}	-0.072^{***}	0.030**	0.025*
	(2.795)	(3.027)	(6.242)	(5.743)	(2.037)	(1.677)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects						
Industry	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,046	9,046	9,046	9,046	9,046	9,046
Adj. R^2	0.13	0.24	0.12	0.18	0.16	0.21

Table D6: Instrumental variables estimates: excluding industry fixed effects

This table replicates the results from Table 2 on the sample of firms with requisite data for the instrumental variables (IV) estimation (Panel A) and from IV regressions that use a measure of firms' exposure to emerging technologies in the late 1980s and early 1990s as an instrument for supplier scarcity, an ex-ante measure of supply network fragility (Panel B). The sample is a firm-year panel of 486 publicly listed U.S. manufacturing firms with global supply networks from 2007 to 2021. *Supplier scarcity* is the additive inverse of the import volume-weighted average number of potential suppliers across import product Harmonized System (HS) codes in a year. *Technology adoption*$_{[1986,1995]}$ is the average frequency of terms related to emerging technologies mentioned in firms' Management Discussion and Analysis (MD&A) section of their 10-K financial reports from 1986 to 1995. The controls in Table 2 are included, but their coefficient estimates are omitted for brevity. All specifications include year fixed effects. 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.

Panel A: Replicated baseline results

	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)
Supplier scarcity$_{t-1}$	0.014**	-0.093^{***}	0.047**
	(2.453)	(3.975)	(2.143)
Controls	Yes	Yes	Yes
Industry	No	No	No
Year	Yes	Yes	Yes
Observations	5,477	5,477	5,477
Adj. R^2	0.15	0.10	0.19

Panel B: IV estimates

	First-stage	Input inventories/assets	Cash/assets	Total debt/assets
	(1)	(2)	(3)	(4)
Technology adoption$_{[1986,1995]}$	0.118***			
	(12.411)			
Supplier scarcity$_{t-1}$		0.039**	-0.171^{***}	0.128***
		(2.097)	(4.354)	(2.770)
Controls	Yes	Yes	Yes	Yes
Fixed effects				
Industry	No	No	No	No
Year	Yes	Yes	Yes	Yes
Observations	5,477	5,477	5,477	5,477
First-stage KP F-statistic		151.15	154.06	151.15
Adj. R^2	0.12			