Hidden Global Risk in Domestic Supply Chains: Evidence from Port Congestion

Haoyuan Ding
College of Business, Shanghai University of Finance and Economics, ding.haoyuan@mail.shufe.edu.cn

Daming Huang
College of Business, Shanghai University of Finance and Economics, hwangdaming@stu.sufe.edu.cn

Shujie Wu
School of Economics, Zhejiang University, shujiewu@zju.edu.cn

Xiaole Wu
School of Management, Fudan University, wuxiaole@fudan.edu.cn

Using high-frequency shipping data, we construct a novel port-level congestion measure and examine how port congestion propagates through domestic supply chains and affects U.S. manufacturers. The central empirical finding is an asymmetry: a manufacturer's own port-congestion exposure has little effect on its sales, whereas congestion faced by its domestic suppliers leads to economically meaningful sales losses. This pattern is robust to an instrumental-variable strategy that uses unexpected port-level wind shocks to isolate exogenous variation in congestion. We then trace the propagation mechanism. First, distributor suppliers play a critical role in shocks transmission, consistent with their role as non-producing intermediaries with limited production flexibility and thin per-SKU inventory buffers; larger focal firms are more resilient, consistent with buyer market power, priority allocation, and more robust supplier relationships. Second, supplier congestion depletes focal firms' inventories, especially raw materials and work-in-process, and pre-shock inventory buffers attenuate the resulting sales decline. Third, the effect is stronger when focal firms operate at high capacity utilization, indicating that limited production slack converts upstream delays into lost sales. Finally, propagation is pronounced when inputs are more relationship-specific and when focal firms belong to time-sensitive industries. The findings challenge the view that domestic sourcing insulates firms from global logistics risk and show that local supply relationships can embed substantial exposure to upstream maritime bottlenecks. This suggests that firms should also watch closely their domestic suppliers, especially distributors, and conduct better inventory management for domestic sourcing.

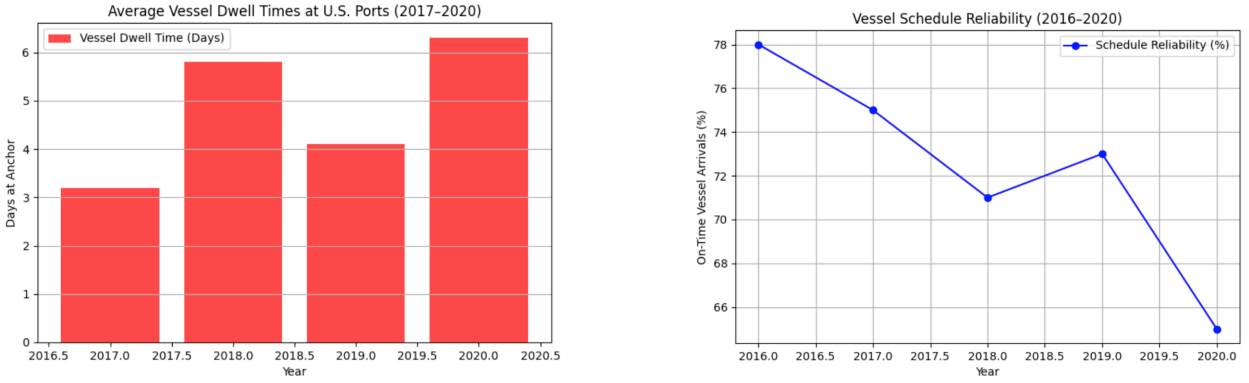
Key words: port congestion, global supply chain, inventory management, maritime shipment

1. Introduction

Global supply chains face a fundamental trade-off: sourcing domestically is seen as safe but costly, while sourcing abroad is cheaper but riskier (Grossman et al. 2023). This distinction has long shaped sourcing strategies and risk management practices in international production networks. However, recent large-scale disruptions have raised questions about whether this conventional dichotomy still holds in modern supply chains (Carvalho et al. 2021, Agca et al. 2022, Acemoglu and Tahbaz-Salehi 2025). As production networks become increasingly fragmented and interconnected, a focal manufacturer can buy from a domestic supplier while that supplier itself relies on imported inputs.

In such a network, a disruption that begins in international transportation can reach a firm that does not directly import, creating an indirect exposure that is difficult to observe and may not be reflected in the focal firm's own risk management decisions. An open question therefore remains: to what extent do disruptions in global logistics affect firms indirectly through their domestic supply chains, and how do these indirect exposures compare to firms' own direct exposure to international shipping risks?

We investigate this question in the context of port congestion, a common yet understudied channel of risk transmission. Among various sources of supply chain disruption, maritime shipping and port congestion play a central role in global supply chains and have received substantial attention in the operations and economics literature (Fransoo and Lee 2013, Bai et al. 2024, Niu et al. 2025, Brancaccio et al. 2025). According to UNCTAD, maritime shipping carries over 80% of global trade volume, and ports are the operational interface through which foreign sourcing enters domestic production networks. When vessel queues, berth constraints, or schedule disruptions slow port operations, the resulting delay can alter the timing and reliability of intermediate-input deliveries.[1] Existing research has documented the consequences of maritime frictions for importers and aggregate outcomes. Less is known about whether these frictions continue to travel through domestic buyer-supplier links after the goods leave the port.



A B

Figure 1 Average Vessel Dwell Time and Vessel Schedule Reliability, 2017–2020

Note: These two figures show the average vessel dwell time and vessel schedule reliability in 2017–2020. From 2017 to 2019, U.S. ports moved from relatively smooth operations into a sharp but temporary congestion episode in late 2018, marked by longer vessel waits, and lower schedule reliability. Source: TradeLanes.

This distinction between direct and indirect exposure is important because two risks induce different operational responses. Firms that import directly observe their own exposure to port conditions

[1] The 2018 congestion surge at U.S. ports offers a telling example of how such systemic risks can materialize. Triggered by capacity constraints and scheduling disruptions, the episode saw truck turnaround times at major ports rise from about 80 to over 90 minutes, container dwell times extend to weeks, and global schedule reliability drop to 70.8% (see Figure 1).

and can invest in mitigation through inventory buffers, supplier diversification, contractual flexibility, rerouting, or expedited transportation (Alessandria et al. 2010, Jain et al. 2022). By contrast, a manufacturer that sources from a domestic supplier may treat that relationship as local and reliable, even when the supplier's own replenishment process is exposed to international shipping. The focal firm may therefore hold insufficient safety stock, lack visibility into the supplier's port exposure, and have limited ability to command priority when a supplier rations scarce inventory. Whether congestion is absorbed by the directly exposed importer or instead propagates downstream is therefore an empirical question.

We answer this question by constructing a two-layer supply-chain panel that links ports, importing suppliers, and downstream U.S. manufacturers. We use high-frequency Automatic Identification System (AIS) vessel-tracking data to build a daily port-level congestion measure based on abnormal vessel-flow "jump" events. We then connect these port-level shocks to firms using Panjiva import records, identify domestic supplier–customer relationships using FactSet Revere, and measure downstream outcomes using Compustat. Our final sample covers publicly listed U.S. manufacturers from 2017Q1 to 2019Q4 and distinguishes between a focal firm's own port exposure, denoted $JumpDays$, and its indirect exposure through domestic suppliers, denoted $SupplierDays$. Figure 2 illustrates the resulting network structure.

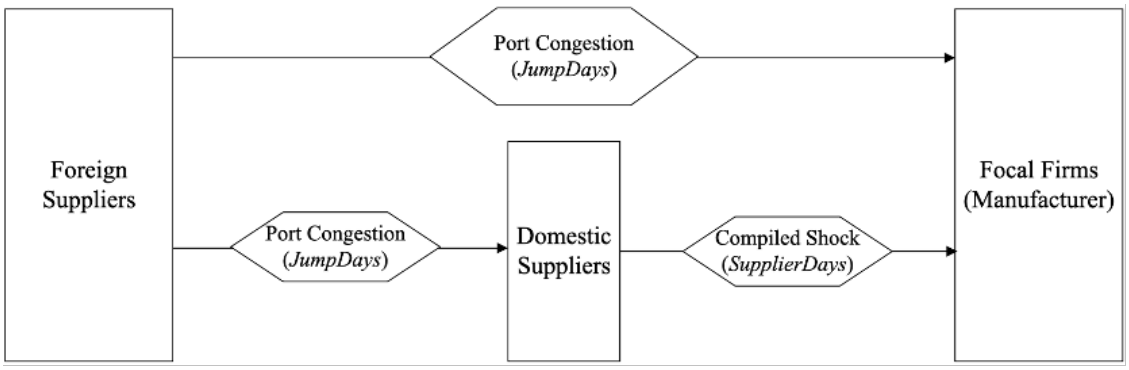


Figure 2 Supply Chain Structure in Our Panel

Note: This figure shows the supply chain relationship in our panel. We include two layers of supply chain relationships. Port congestion shocks can directly influence the performance of U.S. focal firms who import from foreign suppliers, denoted as *JumpDays*. Meanwhile, port congestion shocks faced by domestic suppliers can also propagate to downstream U.S. focal firms, denoted as *SupplierDays*.

Our first result is a pronounced asymmetry between direct and indirect exposure. In dynamic specifications, a focal manufacturer's own port congestion exposure has little effect on its sales. In contrast, congestion faced by its domestic suppliers significantly reduces downstream sales. Quantitatively, a one-day increase in supplier port-congestion days is associated with a 0.51% decline in focal-firm sales. The asymmetry is economically important because it suggests that port shocks are

not simply borne by the firms directly importing through congested ports; rather, they can reappear as delivery shortfalls at the next tier.

To address endogeneity concerns, we implement an instrumental-variable strategy based on port-level daily maximum wind speed. Wind affects vessel maneuvering, berth operations, and port safety protocols, but is plausibly orthogonal to manufacturers' operation and performance. We apply the same jump-event detection method used for vessel flows to daily wind speed and construct $SupplierWindDays$ as an instrument for supplier congestion exposure. The first stage is strong, and the second-stage estimates confirm that supplier port congestion causally reduces focal-firm sales. The IV estimates are larger in magnitude than the OLS estimates, consistent with OLS being attenuated by demand-driven congestion, measurement error in jump detection, and the fact that weather-induced congestion captures particularly acute disruptions.

We then examine the mechanisms through which congestion propagates, following the order of supply and production chains. The first mechanism concerns supplier position and focal-firm size. The effect is concentrated among distributor suppliers. This finding is theoretically informative: because the direct effect of port congestion on manufacturers is weak, manufacturer-suppliers should also be relatively capable of absorbing their own port-side disruptions. Distributors, however, are non-producing intermediaries that aggregate, hold, and resell goods. Their inventory is spread across many SKUs, and they lack production capacity with which to substitute for delayed inbound shipments. As a result, a port-driven shortfall at a distributor can quickly become a stockout for downstream customers. Consistent with this logic, supplier congestion transmitted through distributors has a strong negative effect on focal-firm sales, whereas congestion at manufacturer suppliers and other suppliers has little effect. Within this channel, larger focal firms are more resilient. The evidence is consistent with buyer market power: large firms can command priority when suppliers ration scarce inventory and can form relationships with more resilient suppliers ex ante.

The second mechanism is inventory depletion. Supplier congestion reduces focal firms' total inventory, with the decline concentrated in raw materials and work-in-process inventories. These are precisely the inventory categories that should adjust when upstream delivery delays constrain production. Firms entering the shock with larger pre-shock inventory buffers experience smaller sales losses, showing that inventory absorbs part of the propagated disruption before it reaches output. The third mechanism is production capacity. Firms operating at higher capacity utilization suffer larger sales losses because they have little spare capacity to recover deferred production once deliveries normalize. Limited operational slack therefore converts temporary supplier delays into more persistent output and sales losses.

Finally, we examine two dimensions of heterogeneity across industry characteristics that sharpen the mechanism evidence. The effect is amplified when inputs are more relationship-specific, consistent

with limited substitutability reducing the focal firm's ability to route around a disrupted supplier. It is also stronger in time-sensitive industries, where delays are harder to absorb because products have short life cycles, high turnover, or tight delivery windows. Taken together, these findings challenge the conventional view that domestic sourcing is inherently safer than foreign sourcing. Instead, they highlight that under modern, interconnected supply chain structures, domestic sourcing can embed substantial upstream risk, emphasizing the importance of managing inventory and supplier relationships even when sourcing locally.

The paper contributes to three streams of research. First, we contribute to the operations and economics literature on supply-chain shock propagation by documenting how a temporary logistics bottleneck, rather than a physical disaster or financial shock, travels through domestic production networks. Second, we contribute to the global sourcing literature by showing that domestic sourcing can embed hidden international logistics exposure when domestic suppliers themselves import. Third, we contribute methodologically by combining high-frequency AIS data, shipment records, and supply-chain network data to construct firm-level measures of direct and indirect port-congestion exposure. Together, the results imply that supply-chain risk management should extend beyond a firm's own import operations to the upstream logistics exposure, inventory position, and supplier type of its domestic partners.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on global sourcing, supply chain propagation and maritime logistic failure. Section 3 introduces the data sources and the measurement of variables. Section 4 outlines the empirical specifications, including the instrumental variable strategy employed to identify causal effects, and presents the baseline result. Section 5 discusses mechanism analysis and Section 6 for heterogeneity tests. Section 7 concludes the paper by summarizing the findings and discussing implications for supply chain management.

2. Literature Review

This section reviews three strands of literature: sourcing strategy and inventory management, shock propagation in production networks, and maritime logistics failures. We synthesize these streams to motivate how port congestion shocks transmit through domestic supply chains to affect firm performance.

2.1. Sourcing Strategy and Inventory Management

Sourcing strategy is a fundamental determinant of firm performance, as it defines the structural lead time and risk exposure a firm must manage. Classical inventory theory holds that when lead times are stochastic, firms must maintain safety stock to minimize stockout costs while meeting service levels (Arrow et al. 1951). In a globalized context, the "safety" of a sourcing strategy has traditionally been assessed in terms of distance and reliability. For instance, Grossman et al. (2023)

characterize domestic sourcing as a "safe haven," as it generally entails shorter and less volatile lead times compared to foreign sourcing.

However, the efficacy of these sourcing choices depends on the firm's ability to dynamically manage its inventory. While high-turnover firms can adjust stock levels rapidly to mitigate profit declines (Kesavan et al. 2016), the ability to buffer shocks is not unlimited. Ding et al. (2026) demonstrate that, for firms facing maritime disruptions, inventory serves as the primary adjustment mechanism, yet this buffering capacity is strictly contingent on pre-existing stock levels and financial flexibility. Relatedly, Khan and Khederlarian (2025) show that firms operating in supply chains with greater logistical frictions optimally maintain higher inventory holdings to insure against delays, highlighting inventory as a costly but critical hedge against supply-side uncertainty.

This also creates a complex relationship between micro-level buffering and macro-level propagation. At the firm level, inventories act as critical filters for volatility (Alessandria et al. 2010); yet, when shocks are severe enough to deplete these buffers, the inventory-management process itself can amplify and propagate shocks through the production network (Alessandria et al. 2011). Consequently, the perceived safety of domestic sourcing may be overstated if the domestic tier lacks sufficient internal buffers to absorb upstream logistics failures. Rather than being a static "safe haven," domestic sourcing reliability is a dynamic variable determined by the robustness of inventory buffers across the supply chain.

2.2. Shock Propagation via Supply Chains

A growing body of literature investigates the mechanisms through which localized disruptions escalate into systemic shocks via production networks. At the macro level, research demonstrates that idiosyncratic shocks to a single node can trigger aggregate economic declines through complex input-output linkages (Acemoglu and Tahbaz-Salehi 2025), with recent evidence suggesting these network effects drive long-term inflationary pressures (Alessandria et al. 2023). These theoretical foundations are corroborated by empirical event studies, such as the 2011 Tōhoku earthquake and the COVID-19 lockdowns, which confirm that disasters propagate downstream to affect firms with no direct exposure to the initial event (Carvalho et al. 2021, Lafrogne-Joussier et al. 2022).

The intensity of this transmission is determined by the micro-level characteristics of the buyer-supplier relationship. High input specificity and production rigidity act as amplifiers of propagation, as they limit the ability of downstream firms to substitute away from a disrupted supplier (Barrot and Sauvagnat 2016, Boehm et al. 2019). Furthermore, the structural topology of the network matters: firm-level risk exposure increases monotonically with the proportion of shared suppliers in the network (Wang et al. 2021), while financial distress and credit shocks have been shown to travel both upstream and downstream, creating a "contagion" effect across supply chain links (Agca et al. 2022).

Collectively, these studies establish that supply chain networks serve as a primary conduit for volatility. However, the existing literature focuses heavily on physical disasters or financial insolvency as the "trigger" for propagation. There remains a significant gap in understanding how logistical frictions, specifically maritime port congestion, propagate through these domestic tiers. While a port shock is temporary and non-destructive to physical assets, its ability to disrupt the flow of intermediates may follow the same vertical logic identified in the network literature, potentially creating "hidden" risks for firms that believe their domestic sourcing strategy insulates them from global logistics failures.

2.3. Maritime Shipment and Logistics Failure

Given that over 80% of global trade volume and 50% of trade value relies on ocean transport, maritime logistics represents a primary bottleneck in international production (Verschuur et al. 2023). Empirical evidence establishes that transport time is a significant non-tariff trade barrier, with each day of delay equivalent to a substantial ad-valorem tariff (Hummels and Schaur 2013). These delays are increasingly driven by exogenous operational and environmental risks, such as higher wind speeds and wave heights, which significantly increase ship-incident risks and port detention times (Heij and Knapp 2015). Ding et al. (2026) further quantify this impact by demonstrating that climate-induced port disruptions increase transit times by 8–11%, directly degrading the profitability and ROA of firms that rely on these maritime gateways.

The economic consequences of these frictions extend beyond the port of entry due to the structure of modern intermediation. The rise of "superstar wholesalers" has been driven by their ability to achieve economies of scale in global sourcing and domestic distribution (Ganapati 2025). By bridging the gap between foreign suppliers and domestic buyers, these intermediaries consolidate maritime risks. While ocean container transport is recognized as a key bottleneck affecting trade flows and delivery times (Fransoo and Lee 2013), the focus has traditionally remained on firms with direct import exposure. This leaves an unexplored gap regarding how these logistics frictions penetrate the domestic economy through wholesalers, affecting downstream firms that lack direct visibility into the port-level disruptions.

Collectively, the literature suggests that, while inventory and sourcing strategies are designed to insulate firms (Ding et al. 2026, Alessandria et al. 2010), the physical reality of maritime bottlenecks creates a "ripple effect" that bypasses direct importers. Different from Bai et al. (2024) focusing on macro impact of port congestion on inflation, we explore the micro evidence that port congestion shocks faced by upstream intermediaries may transmit supply variability through the network, leading to worse performance of downstream manufacturers. This highlights a critical gap: the literature has yet to quantify how these "hidden" logistics risks penalize downstream domestic firms that believe they are insulated from global maritime volatility by virtue of sourcing locally.

The three strands above converge on a single tension that motivates our analysis. The sourcing literature frames the choice between international and domestic suppliers as a risk–return trade-off, with an implicit corollary that domestic sourcing insulates the focal firm from international logistics frictions such as port disruption (Grossman et al. 2023). In modern, interconnected production networks, however, this insulation is incomplete: many domestic suppliers are themselves importers whose intermediate inputs arrive through U.S. ports, so a port disruption that strikes an upstream domestic supplier is in effect an international logistics shock transmitted one node downstream. This propagation is unlikely to be symmetric across tiers. Manufacturing importers absorb the direct impact through buffer inventories of imported intermediates, whereas downstream focal manufacturers contract on the assumption that domestic deliveries are reliable, hold thinner input safety stocks, and lack the relational depth to command priority when capacity is rationed. The direct impact on the focal firm is thus muted by mitigation, while the indirect impact, against which the focal firm has not buffered, dominates. The remainder of the paper takes this propagation argument to the data: we first establish that upstream port-congestion shocks transmit downstream to focal-firm sales, and then unpack the mechanisms that govern this transmission including supplier type and focal-firm size, inventory depletion and the pre-shock inventory buffer, and production capacity together with its heterogeneity across input specificity and time sensitivity.

3. Data and Variable Construction

To construct a comprehensive dataset linking port-congestion to firm performance along the supply chain, we integrate multiple data sources: (1) S&P Panjiva bill of lading data for linking port situation to firms, (2) Automatic Identification System (AIS) data for measuring port congestion, (3) FactSet Revere for domestic supply chain relationship, and (4) Compustat for company fundamentals.

3.1. S&P Panjiva Bill of Lading

We draw on transaction-level supply chain and shipping records from Panjiva, with a particular focus on U.S. import transactions. The Panjiva U.S. import dataset is constructed from official customs filings and shipping manifests, offering detailed coverage of individual shipments entering the United States. Each record contains rich information on trading partners, including the identities and locations of foreign suppliers and U.S. importers, as well as comprehensive descriptions of the shipped products, such as weight, quantity, declared value, product descriptions, and Harmonized System (HS) classifications.

In addition to product-level details, the dataset reports extensive logistics information. This includes ports of lading and unlading, and associated geographic regions, along with carrier- and vessel-level identifiers. These features allow us to follow individual import shipments from their origin through maritime transport to their arrival at U.S. ports. The granularity of the data enables us

to trace shipment-level import activities of U.S. firms and link logistics outcomes to firm behavior. For instance, the dataset records shipments in which firms import specific products from identified overseas suppliers via named vessels, together with precise arrival dates and port information. This structure allows us to connect the shipment situation to firm-level outcomes and performance.

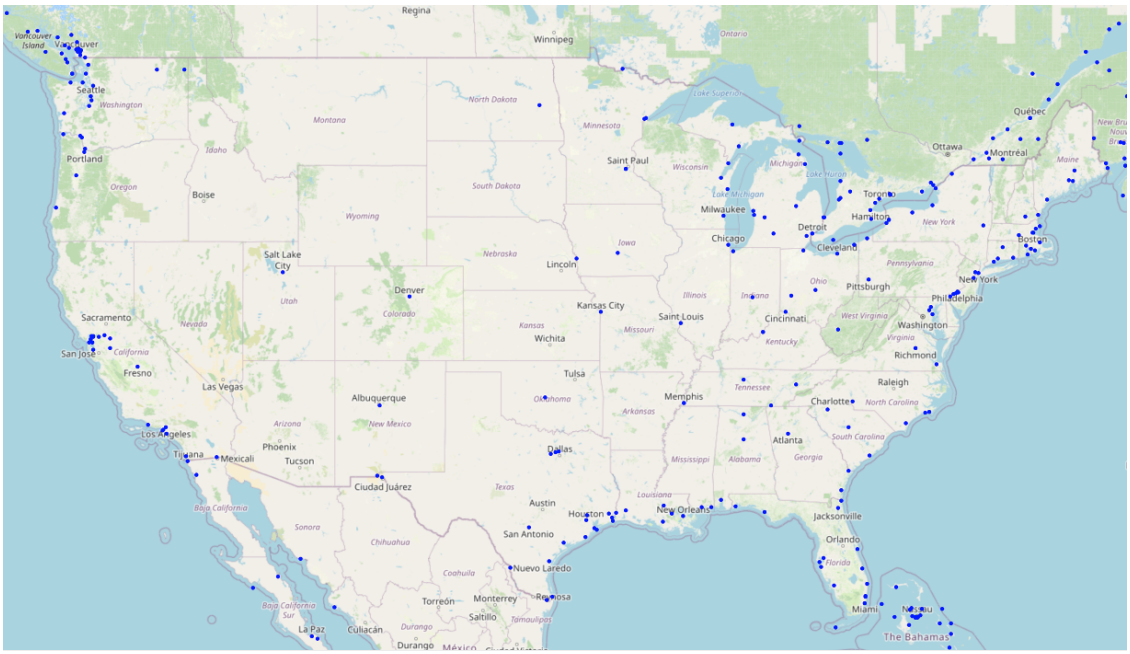


Figure 3 Distribution of U.S. Mainland Ports in Panjiva

Note: This figure shows the distribution of U.S. mainland ports in Panjiva. Panjiva contains detailed port information with about 130 ports in the U.S. mainland, most of which are located at the seaside and very few at the riverside.

A key strength of the Panjiva data is its detailed port coverage. The U.S. import records span approximately 130 ports in the U.S. mainland, predominantly seaports with a small number of inland river ports, which facilitates a precise study of the port situation (see Figure 3). Owing to these features, the Panjiva dataset has been widely used in recent studies of international trade and global supply chains, including Charoenwong et al. (2023), Jain and Wu (2023), and Niu et al. (2025).

3.2. Automatic Identification System (AIS) Data

We also utilize high-frequency vessel-tracking data from the Automatic Identification System (AIS) to construct the port congestion index. The AIS dataset covers the complete stream of vessel broadcasts between 2017 and 2019 and includes over 140,000 distinct commercial vessels, identified by unique Maritime Mobile Service Identity (MMSI) numbers.

Each AIS message contains two types of information. The first consists of time-invariant vessel characteristics, such as vessel name, International Maritime Organization (IMO) number, ship type, and physical dimensions. The second captures time-varying navigational states, including geographic

coordinates (latitude and longitude), speed, heading, navigation status, and precise timestamps. These repeated broadcasts generate a continuous record of vessel movements over time.

The high spatial and temporal resolution of AIS data allows us to directly measure daily vessel flows at the port level based on spatial proximity and navigation status. We compute the vessel activities concentrated on 36 major hubs, which account for over 85% of the U.S. maritime imports recorded in Panjiva. Aggregating these arrivals over the 2017–2019 period produces the port-level intensity patterns shown in Figure 4, highlighting major gateways such as Los Angeles and Seattle on the West Coast, New York on the East Coast, and Houston along the Gulf Coast.

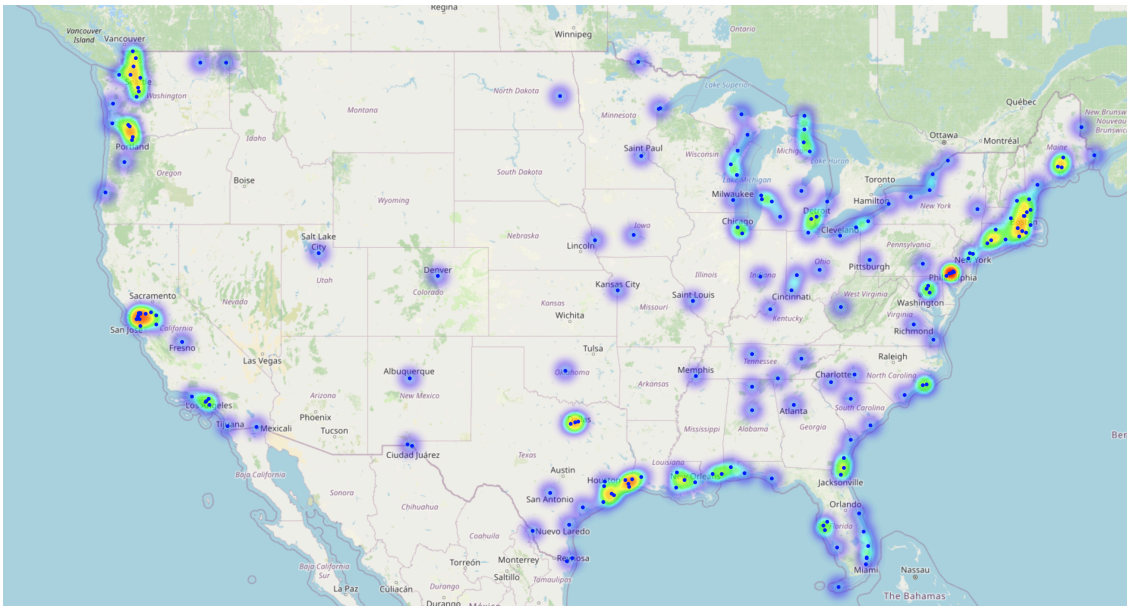


Figure 4 Heatmap of Vessel Activities in U.S. Mainland Ports

Note: This figure shows the heatmap about vessel activities intensity in U.S. mainland ports calculated by the daily vessel flows using AIS. Intense vessel activities concentrate in Seattle, San Francisco, and Los Angeles on the West Coast, New York on the East Coast, and Houston on the South Coast.

3.3. FactSet Revere Database

Our firm-level domestic supply chain information is drawn from the FactSet Revere database, a widely used source in recent research on global supply chains (e.g., Charoenwong et al. 2023; Ding et al. 2023). FactSet Revere systematically compiles supplier–customer linkages worldwide by aggregating information from multiple primary disclosures, including regulatory filings (such as SEC Forms 10-K, 10-Q, and 8-K), investor presentations, company websites, and press releases.

On average, FactSet Revere contains over 25,000 buyer-supplier links per year for U.S. public firms, far exceeding the limited scope of disclosure-based Compustat. Thus, FactSet Revere provides a substantially more complete representation of firms' upstream and downstream production networks. In

order to identify the U.S. domestic supply chain network, we merge FactSet Revere with Worldscope to identify U.S. listed firms.[2]

3.4. Firm-level Variables Construction

According to daily shipment flows of U.S. ports calculated through AIS data, we follow the methodology of Bloom (2009) to detect "jump events" to identify the port congestion shock. Specifically, we first apply a Hodrick-Prescott (HP) filter to the logarithm value of daily shipment flows with a one-week moving average and identify a jump event when the value exceeds the HP-filtered volume by more than 1.96 standard deviations (above the 95% confidence interval).[3] These jump events serve as our proxy for port congestion, indicating sudden and prominent operational bottlenecks.[4]

We then construct the firm-specific direct exposure to the port congestion shock utilizing Panjiva. If a firm's imports arrived at the impacted port on that congestion date, we perceived the firm receiving a direct congestion shock once. To map with quarterly firm-level fundamental variables, we aggregate the congestion days count of a firm within a quarter, denoted as $JumpDays_{it}$, following Pankratz and Schiller (2024). For robustness, we compute the total impacted port congestion times as $JumpSum_{it}$, which aggregate the numbers of congestion events within a quarter.

We also construct the firm-specific indirect exposure to the port congestion shock transmitted from domestic suppliers by link to the supply-chain datasets from FactSet Revere. We compute the unique jump days experienced by a focal firm's domestic suppliers to create the variable $SupplierDays_{it}$. This measure is our key ingredient in empirical analysis and allows us to capture how port congestion shocks faced by domestic suppliers propagate to downstream U.S. focal firms. Similarly, we calculate the total times of indirect port congestion shocks from domestic suppliers denoted as $SupplierSum_{it}$ for later robustness check.

We obtained the firm-level fundamentals from Compustat, which is the standard source for quarterly-based financial statements for all U.S. publicly listed firms. Throughout our analysis, the primary measure of the firm-level outcome variable is sales scaled by lagged assets from the same quarter of the previous year, which is denoted as *Sales* and indicates the sales performance of focal

[2] FactSet Revere identifies supply chain links at the firm level and does not consistently distinguish between parent firms and foreign subsidiaries. Consequently, some suppliers classified as U.S. firms may conduct the relevant production or logistics activities through non-U.S. affiliates, even though the U.S. parent does not have a direct operational relationship with the focal firm. This may introduce measurement error in identifying domestic supply chains. However, supply chain relationships are highly localized, and suppliers and customers are more likely to operate within the same country. Moreover, parent firms typically coordinate sourcing and inventory decisions across subsidiaries, implying that upstream transportation shocks can still be transmitted to downstream firms. Any resulting measurement error is therefore likely to attenuate our estimates rather than bias them upward.

[3] Bloom (2009) uses the threshold of 1.65 standard deviation for quarterly data which stands for 90% confidence interval. Since we use the daily data with higher frequency and larger noise than Bloom (2009), we apply a stricter threshold of 1.96 standard deviation indicating the 95% confidence interval. Our results stay robustness if we align the thresholds with Bloom (2009).

[4] As shown in Figure A1, the blue line is the logarithm value of the moving average daily shipment flows in the port of Houston in 2017. The red dots are the jump events indicating that the Port of Houston has suffered a significant port congestion shock in August and September 2017.

firms. In mechanism analysis, we also construct dependent variables for total inventory ($INVT$), raw material inventory ($INVR$), work-in-process ($INVW$), and finished goods ($INVF$), all scaled by total assets as measures of different inventory management.

$$
\begin{aligned}
Sales_{i,t} &= Total\ Sales_{i,t}/Total\ Assets_{i,t-4} \\
INVT_{i,t} &= Total\ Inventory_{i,t}/Total\ Assets_{i,t-4} \\
INVR_{i,t} &= Raw\ Materials\ Inventory_{i,t}/Total\ Assets_{i,t-4} \\
INVW_{i,t} &= Work\ in\ Process\ Inventory_{i,t}/Total\ Assets_{i,t-4} \\
INVF_{i,t} &= Finished\ Goods\ Inventory_{i,t}/Total\ Assets_{i,t-4}
\end{aligned}
$$

Following the related literature on firm behavior and performance (Ding et al. 2023), we include a standard set of firm-level covariates to account for heterogeneity in scale, financial conditions, and operating performance. Firm size ($Size$) is proxied by the logarithm of total assets, which captures differences in production capacity, market presence, and organizational scale. Financial leverage (Lev) is measured as total liabilities divided by total assets, controlling for variation in capital structure and exposure to financial risk. We also control for profitability using return on assets (ROA), defined as net income relative to total assets, which reflects firms' operating efficiency and overall financial health. All firm-level controls are included with a lag. This timing structure helps reduce concerns about reverse causality and limits the influence of contemporaneous shocks to firm fundamentals on the estimated effects of interest.

To examine how shocks propagate through domestic supply chains, our main sample focus on U.S. manufacturing firms.[5] After integrating data from Panjiva, AIS, FactSet Revere, and Compustat, our final regression sample consists of 19,850 firm-quarter observations covering 1,925 publicly listed U.S. manufacturers over the period from 2017Q1 to 2019Q4. Table 1 reports summary statistics for the key variables used in the empirical analysis, including the number of observations, mean, standard deviation, minimum, median, and maximum values. Detailed variable definitions and data sources are provided in Table A1.

4. Empirical Strategy and Results

Leveraging the datasets constructed above, we first show the preliminary empirical evidence on the propagation effects of port congestion shocks via supply chain network. Subsequently, we focus on the effects of indirect shocks on focal firms propagated from domestic suppliers and use an instrumental variable for casual inference.

[5] Manufacturers typically rely on both foreign and domestic input suppliers and tend to exhibit higher inventory sensitivity due to the requirements of continuous production processes (Esposito et al. 2024). Besides, for further analysis, we can separate the total inventory of manufacturers into raw materials, work in process, and finished goods to explore the underlying mechanism using Compustat dataset while other firms cannot provide detailed inventory information classified into different categories.

Table 1 The Summary Statistics of All Variables

Variable	Obs.	Mean	SD	Min	p50	Max
Dependent Variables						
Sales	19,850	0.213	0.215	0	0.179	1.588
INVT	19,768	0.129	0.140	0	0.098	0.752
INVR	17,219	0.047	0.065	0	0.024	0.312
INVF	17,327	0.057	0.080	0	0.031	0.501
INVW	17,092	0.021	0.038	0	0.004	0.189
Independent Variables						
JumpDays	19,850	0.099	0.688	0	0	17
SupplierDays	19,850	0.331	1.587	0	0	20
SupplierWindDays	19,850	0.419	1.692	0	0	26
SupplierDays_MFT	19,850	0.228	1.251	0	0	19
SupplierDays_DIS	19,850	0.062	0.766	0	0	17
SupplierDays_OTS	19,850	0.071	0.651	0	0	16
JumpSum	19,850	0.205	2.094	0	0	112
SupplierSum	19,850	1.449	17.343	0	0	1,569
Control Variables						
Size	19,616	5.348	2.830	-3.297	5.448	11.317
ROA	19,595	-0.177	0.725	-6.327	-0.005	0.227
Lev	19,616	1.237	4.650	0.026	0.501	43.572
Other Variables						
PreINVT	17,621	0.131	0.140	0	0.100	0.755
PreINVR	15,292	0.048	0.066	0	0.025	0.314
PreINVNR	14,825	0.077	0.090	-0.031	0.052	0.693
CapacityUtilize	18,946	2.885	9.883	0	1.027	116.368
ContractIntensity	12,085	0.609	0.226	0.024	0.694	0.980
Sensitive	19,850	0.254	0.435	0	0	1
Insensitive	19,850	0.074	0.262	0	0	1
BigSize	19,850	0.405	0.491	0	0	1

Notes: This table shows the summary statistics of our quarterly firm-level panel. Detailed definition and data sources of each variable are shown in Table A1. Firm-level outcome variables and control variables are winsorized at 1% and 99%.

4.1. Propagation of Port Congestion Shocks

To investigate whether port congestion shocks propagate from suppliers to downstream customers, we construct a dynamic regression model, separating the direct impact of port congestion on focal firms from the indirect effects propagated through their domestic suppliers. We illustrate this two-layer supply chain structure in our conceptual framework (see Figure 2) in spirit of Barrot and Sauvagnat (2016), where foreign exporters feed into domestic suppliers who in turn supply the focal U.S. manufacturers.

$$Sales_{it} = \sum_{k=0}^{2} (\beta_{1,k} \times JumpDays_{i,t-k} + \beta_{2,k} \times SupplierDays_{i,t-k}) + \gamma_1 Size_{i,t-1} + \gamma_2 Lev_{i,t-1} + \gamma_3 ROA_{i,t-1} + \delta_i + \omega_t + \varepsilon_{i,t}, \quad (1)$$

where $Sales_{it}$ is the dependent variable, defined as the quarterly sales of firm i in quarter t, scaled by total assets from the same quarter of the previous year to control for size and seasonality. $JumpDays_{it}$ represents the direct port congestion shock, measured as the number of unique days the focal firm's own import ports experienced congestion. $SupplierDays_{it}$ represents the aggregated port congestion

shocks experienced by the focal firm's domestic suppliers. We control three major lagged firm-level variables to account for prior firm conditions and mitigate potential endogeneity, which are firm size ($Size$), leverage (Lev), and return on assets (ROA), with clustering at industry (SIC three-digit) and state level for the spatial and industrial correlation. We also incorporate a vector of fixed effects in our estimation to ensure the rigorousness of our specification, including firm-quarter FE, industry-year-quarter FE, state-year-quarter FE and quantile FE.

We are particularly interested in the coefficient $\beta_{1,k}$ and $\beta_{2,k}$, and both are expected to be negative. We are also interested in the magnitude comparison between these coefficients. If the absolute value $\beta_{2,k}$ is greater than that of $\beta_{1,k}$ (given k), it indicates the congestion shocks reinforced itself along the supply-chain to the downstream. Otherwise, it indicates the congestion shocks is absorbed in the supply chain.

4.2. Baseline Results of the Dynamic Effect

Table 2 presents the dynamic OLS estimates of Eq. 1. The estimation results reveal some intriguing evidence. First of all, the coefficients $\beta_{1,k}$ are generally statistically insignificant across lagging time periods, indicates the direct exposure to the port congestion shocks not necessarily lead to a decline in import firms' outputs. Second, the coefficients $\beta_{2,k}$ are statistically significant and larger in magnitude, showing that the indirect exposure to the port congestion shocks would adversely affect focal firms' performances. Particularly, the lagged term $\beta_{2,1}$ exhibits systematic negative coefficients across all specifications. The magnitude is also economically meaningful. For example, according to column (2), a one-day increase in suppliers' port congestion days leads to a 0.51% decrease of focal firm's sales.[6] These findings challenge the conventional intuition that domestic sourcing shields firms from international logistics risks; instead, they suggest a ripple effect of maritime shocks along the supply chain. Focal firms that source from domestic importers, are more vulnerable to the maritime bottlenecks through indirect exposure.

The absence of significant effects from firms' direct exposure to port congestion, alongside strong and persistent spillovers through upstream suppliers, can be rationalized by differences in adjustment margins and buffering capacity across firms. Importing firms that are directly exposed to port congestion are typically larger, more experienced in international sourcing, and better equipped to absorb short-term logistics disruptions through inventory buffers, supplier diversification, contractual flexibility, and mode-switching (such as rerouting or expedited shipping). As a result, the immediate impact of port congestion shocks on their output is largely mitigated.

In contrast, downstream firms that source inputs domestically from importing suppliers face indirect exposure that is harder to anticipate and insure against. When upstream suppliers experience

[6] A one-day increase in suppliers' port congestion days leads to a decrease of approximately 0.52% (0.0011/0.213×100%=0.52%) of focal firm's sales.

port congestion, they may respond by rationing output, prioritizing key customers, delaying deliveries, or passing through higher costs. These upstream adjustments propagate along domestic supply chains and translate into effective input shortages or higher input prices for downstream firms, which typically hold lower inventories of intermediates and have less flexibility in adjusting sourcing strategies in the short run. Consequently, maritime congestion shocks that are absorbed at the importer level re-emerge downstream, leading to economically meaningful declines in firm performance.

Besides, while focal manufacturers may have better inventory storage that buffers direct port congestion shocks, domestic suppliers include other types of enterprises, such as retailers and wholesalers which are also sensitive to supply chain disruption. The shock propagated from these distributors may cause a greater impact on downstream customers. Here we leave for later underlying mechanism and heterogeneity analyses.

Table 2 The Dynamic Impact of Port Congestion on Firm Sales

VARIABLES	*Sales*			
	(1)	(2)	(3)	(4)
JumpDays	0.0003	0.0002	0.0005	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
L.JumpDays	-0.0003	-0.0010	-0.0006	-0.0011
	(0.001)	(0.001)	(0.001)	(0.001)
L2.JumpDays	-0.0013*	-0.0014	-0.0009	-0.0015*
	(0.001)	(0.001)	(0.001)	(0.001)
SupplierDays	-0.0009	-0.0011**	-0.0010**	-0.0012**
	(0.001)	(0.000)	(0.000)	(0.000)
L.SupplierDays	-0.0012**	-0.0011**	-0.0011***	-0.0011**
	(0.001)	(0.000)	(0.000)	(0.000)
L2.SupplierDays	-0.0002	-0.0004	-0.0004	-0.0004
	(0.000)	(0.000)	(0.001)	(0.000)
L.Size				0.0091
				(0.011)
L.Lev				0.0019*
				(0.001)
L.ROA				0.0130***
				(0.004)
Observations	19,824	19,776	19,734	19,447
R-squared	0.817	0.821	0.832	0.824
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE		Yes	Yes	Yes
Quantile FE			Yes	
Firm Controls				Yes

Notes: This table shows the OLS result of dynamic impacts of port congestion on focal firms' sales. *JumpDays* is the unique port congestion days faced by focal firms themselves while *SupplierDays* is the unique port congestion days faced by focal firms' suppliers. The dependent variable is focal firms' sales scaled by the total assets in the same quarter last year, denoted as *Sales*. We include three periods of shocks in the regression to study dynamic impact of shocks. We also control different levels of fixed effects including Firm-Quarter, Industry-Year-Quarter, State-Year-Quarter, firm size and ROA Quantile FE as well as firm level time-varying control variables in different columns. Results show that port congestion shock faced by domestic suppliers can propagate via supply chain leading to sales decrease of downstream manufacturers. The above impact lasts for two quarters and is more robustly significant in next quarter. Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3. Identification Strategy: IV Estimation

Although port congestion is largely driven by external operational and infrastructure constraints, OLS estimation is subject to three identification threats that bias $\hat{\beta}_{OLS}$ toward zero: (1) Reverse causality from demand to congestion. When firm i's end-market demand strengthens, the firm and its peers place larger input orders, raising container throughput at the ports through which their suppliers ship and pushing those ports closer to their capacity frontier. The resulting dwell-time spike is mechanically classified as a congestion shock, so $SupplierDays_{it}$ is itself partly a function of firm i's demand realization which also raises $Sales_{it}$; (2) Omitted demand shocks. Sector- or region-specific demand booms simultaneously elevate import volumes (worsening port congestion) and downstream revenues. Our firm, industry-by-quarter, and state-by-quarter fixed effects absorb a substantial portion of this variation, but cannot rule out finer-grained shocks that comove with both regressor and outcome; (3) Endogenous sourcing and measurement error. Firms self-select into supplier and port networks that correlate with their growth trajectory, and the jump-event detector inevitably contains classification noise. The first channel induces an additional positive bias; the second produces classical attenuation toward zero.

To address these concerns, we instrument $SupplierDays_{it}$ with $SupplierWindDays_{it}$, a measure of firm i's indirect exposure to unexpected wind events at supplier ports constructed by applying the same jump-event detection method to daily maximum wind speed at each port. The instrument is plausibly excludable: localized wind shocks affect vessel maneuvering, berthing operations, and port safety procedures, thereby disrupting supplier shipping, but are unlikely to affect downstream manufacturers' sales through any other channel, because the focal firms are physically removed from the ports and the events themselves are too short-lived and geographically narrow to enter firm-level revenue through direct property, labor-market, or local-demand channels. The remaining fixed-effect structure absorbs common regional and industry shocks, so identification is driven by within-firm variation in highly localized port weather.[7]

Accordingly, the port congestion shock, $SupplierDays_{it}$, should be positively correlated with the shock of port-level extreme wind speed, $SupplierWindDays_{it}$. For tractability of the 2SLS estimation, we adopt a parsimonious one-lag specification rather than the distributed-lag form used in the OLS baseline:

$$Sales_{i,t} = \beta_1 \widehat{SupplierDays}_{i,t-1} + \gamma_1 Size_{i,t-1} + \gamma_2 Lev_{i,t-1} + \gamma_3 ROA_{i,t-1} + \delta_i + \omega_t + \varepsilon_{i,t}, \qquad (2)$$

[7] A natural concern is that wind shocks coincide with hurricanes, which could violate the exclusion restriction by affecting firm operations directly. At the port-day level, we identify 749 jump-wind days across our sample, of which only 38 (5.1%) overlap with hurricane exposure. The instrument's identifying variation therefore comes overwhelmingly from non-hurricane wind fluctuations. Figure A1 illustrates this for the Port of Houston in 2017, where wind-based jump events line up with the post-Harvey reopening period.

where the first stage regression is:

$$SupplierDays_{i,t-1} = \beta_1 SupplierWindDays_{i,t-1} + \gamma_1 Size_{i,t-1} + \gamma_2 Lev_{i,t-1} + \gamma_3 ROA_{i,t-1} + \delta_i + \omega_t + \varepsilon_{i,t}. \quad (3)$$

The results of the IV estimation are reported in Table 3. In columns (1) and (2), we report the first-stage estimation results, while in columns (3) and (4) we report the second-stage estimation results. From estimation results in columns (1) and (2), we confirm that the instrument variable $SupplierWindDays_{it-1}$ is strongly positively correlated with $SupplierDays_{it-1}$, exhibiting strong relevance. The corresponding Kleibergen-Paap F statistics are also well above the threshold of 10, indicating no weak instrument problem. The second-stage estimation results shown in columns (3) and (4) show that, focal firms' indirect exposure to the congestion shocks lead by extreme weather have a negative impact on the firms' real outcomes, consistent with that in the OLS estimation in Table 2. The coefficient of -0.0086 suggests that a one-day increase in suppliers' port congestion days due to unexpected exogenous wind shocks leads to approximately 4.04% decrease in the focal firm's sales.

Notably, the 2SLS estimate is larger in magnitude than the corresponding OLS coefficient, a pattern consistent with all three identification threats discussed above. First, the IV purges the positive bias from demand-driven congestion and omitted sectoral demand shocks, which mechanically attenuate $\hat{\beta}_{OLS}$ toward zero. Second, classical attenuation from measurement error in $SupplierDays_{it}$ is also corrected, as the instrument is independent of the classification noise in the endogenous regressor. Third, 2SLS recovers a Local Average Treatment Effect (LATE) among firms whose supplier congestion is shifted by extreme wind events, and weather-induced disruptions tend to be more acute, less anticipated, and harder to mitigate through inventory buffering or expedited rerouting than the average congestion event, so the per-day output loss on the firm subpopulation is plausibly larger than the population-average effect estimated by OLS (Card 2001).

Here we also conduct a robustness check by replacing the measurement of port congestion shocks. First, we use the same threshold of 1.65 standard deviation to identify jump events of port congestion aligned with Bloom (2009). Second, instead of computing the unique shock days, we measure the total time of port congestion shocks suffered by focal firms directly and their corresponding domestic suppliers. As is shown in Table A4 and Table A5, both OLS and IV results of the negative impact of suppliers' port congestion shocks on focal manufacturers' sales still hold. The shrinking coefficients in Table A5 are due to the increasing value of total times compared to unique days.

Table 3 The 2SLS Estimation of Suppliers' Port Congestion on Firm Sales

VARIABLES	*L.SupplierDays*		*Sales*	
	(1)	(2)	(3)	(4)
	1st-stage		2nd-stage	
L.SupplierWindDays	0.2024***	0.2017***		
	(0.028)	(0.028)		
L.SupplierDays			-0.0086**	-0.0086**
			(0.004)	(0.004)
L.Size		-0.0171		0.0089
		(0.014)		(0.011)
L.Lev		-0.0022		0.0019*
		(0.003)		(0.001)
L.ROA		-0.0137		0.0129***
		(0.015)		(0.004)
Observations	19,786	19,457	19,786	19,457
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Controls		Yes		Yes
KP F Statistics			53.24	53.70

Notes: This table shows the result of 2SLS estimation by using the *SupplierWindDays* as the instrument variables. The endogenous variable is *SupplierDays* and the dependent variable is *Sales*. Columns (1) and (2) show the first stage results of 2SLS estimation indicating significant correlation between *SupplierDays* and *SupplierWindDays*. Columns (3) and (4) show the second stage results of 2SLS estimation. The significant results of second stage estimation indicates that if the port congestion day of domestic suppliers increases one day due to heavy wind, then the sales of focal manufacturers decrease 4.04% on average. The KP-F statistics are above 10 indicating there is no weak IV problem. Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5. Mechanism Analysis

Our mechanism analysis proceeds along three complementary dimensions, each isolating a distinct link in the chain that runs from an upstream port-congestion shock to the focal manufacturer's sales decline. This first mechanism asks where in the supplier base the shock originates and which focal firms are able to insulate themselves from it: we show that propagation is concentrated among distributor suppliers and that it is borne disproportionately by smaller focal firms. The two subsequent mechanisms then trace the channel inside the focal firm, documenting the role of inventory buffers (Mechanism 2) and of production capacity (Mechanism 3). Throughout, our point of departure is a salient feature of the baseline results: a firm's own direct port exposure, $JumpDays$, is economically and statistically weak, consistent with importing manufacturers absorbing their own port-side disruptions through buffer stocks of imported inputs.

5.1. Supplier Type and Firm Size

The baseline results pose an immediate puzzle. If a focal manufacturer's own port exposure does not measurably depress its sales, why should congestion transmitted from its suppliers do so? This first mechanism resolves the puzzle by decomposing the origin of the indirect shock across supplier types and then asking which focal firms are best positioned to withstand it.

5.1.1. The Distributor Channel. The weakness of the direct effect is itself informative about how shocks should and should not travel through the network. If a focal manufacturer can absorb its own port disruption internally, then by symmetry an upstream manufacturer-supplier struck by the same kind of shock should also buffer it on its own balance sheet and transmit little downstream. Manufacturer-to-manufacturer propagation should therefore be roughly as weak as the direct effect it mirrors, and the transmission we document in the baseline must originate elsewhere in the supplier base. The natural candidate is the distributor tier. Distributors are non-producing intermediaries that purchase, hold, and resell goods without transforming them, performing a coordination rather than a production function (Spulber 1996, Bernard et al. 2010). Because their inventory is spread across a broad assortment, per-SKU depth is limited even when aggregate inventories are large (Fisher 1997). A distributor holds no production capacity that could substitute for a delayed inbound shipment and no meaningful per-SKU cushion, so a port-driven shortfall in inflows converts almost immediately into a stockout against the next downstream order. Distributors are thus the node at which a supply shock is most likely to be passed through to the focal firm.

To test this, we classify each focal firm's domestic suppliers into manufacturers (MFT), distributors (DIS), and others (OTS), and re-estimate the dynamic OLS specification in Eq. 1 and the 2SLS second stage in Eq. 2 with indirect exposure decomposed by supplier type. The results in Table 4 are sharp: the coefficient on $SupplierDays_DIS$ is negative and statistically significant in both the OLS and the IV columns, whereas the coefficients on $SupplierDays_MFT$ and $SupplierDays_OTS$ are indistinguishable from zero. The propagation documented in the baseline is therefore driven by congestion shocks reaching the focal firm through its distributor suppliers, exactly the node our reasoning identifies as least able to buffer the shock internally.

5.1.2. Firm Size and Buyer Market Power. Having identified the source of the shock, we turn to which focal firms can withstand it. The capacity to insulate against a propagated supply shock should rise with firm scale, operating through buyer market power along two margins. Ex post, during a congestion episode, a large focal firm commands priority in the rationing of scarce supply: its order volume, the value of its repeat business, and its bargaining leverage induce distributors to fill its orders ahead of smaller customers. Ex ante, a larger firm has the resources and the supplier-search capability to assemble a more resilient supply base in the first place, through multi-sourcing, qualifying backup suppliers, and selecting partners with deeper inventories and more reliable logistics, so that a given port shock is less likely to bind on its deliveries. Both margins imply that propagation is attenuated for larger firms. We emphasize that this prediction is the opposite of what would obtain if firm scale merely proxied for leaner, lower-buffer operations, which would make large firms more exposed; the sign of the size effect is therefore a discriminating test.

Table 4 The Heterogeneity Analysis of Suppliers' Types

VARIABLES	*Sales*			
	(1)	(2)	(3)	(4)
Panel A: OLS				
L.JumpDays	-0.0005	-0.0012	-0.0007	-0.0014
	(0.001)	(0.001)	(0.001)	(0.001)
L.SupplierDays_MFT	-0.0004	-0.0006	-0.0005	-0.0007
	(0.001)	(0.001)	(0.001)	(0.001)
L.SupplierDays_DIS	-0.0033***	-0.0030***	-0.0029***	-0.0026**
	(0.001)	(0.001)	(0.001)	(0.001)
L.SupplierDays_OTS	0.0006	0.0002	0.0003	0.0003
	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.817	0.821	0.832	0.824
Observations	19,834	19,786	19,744	19,425
Panel B: IV				
L.SupplierDays_DIS	-0.0077*	-0.0077*	-0.0066*	-0.0073*
	(0.004)	(0.004)	(0.004)	(0.004)
KP F Statistics	44.70	44.82	47.70	45.44
Observations	19,834	19,786	19,744	19,457
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE		Yes	Yes	Yes
Quantile FE			Yes	
Firm Controls				Yes

Notes: This table shows the heterogenous analysis of suppliers' types. We classify focal firms' suppliers into three types according to SIC code: manufacturers (*MFT*), distributors (*DIS*, including retailers and wholesalers), and others (*OTS*). We calculate the *SupplierDays* and *SupplierWindDays*, respectively. We include three types of suppliers' shocks in the regression. Both OLS and IV results show that shocks from domestic distributor suppliers have the prominent impact on focal firms' sales. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in the column (4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We split the sample at the median of total assets and re-estimate Eq. 1 and Eq. 2 within each subsample. Table 5 shows that the negative effect of $SupplierDays_DIS$ is concentrated among smaller firms, in both the OLS and IV columns, while larger firms display no statistically significant sensitivity to the propagated shock. Larger focal firms thus bear essentially none of the propagation, consistent with greater resilience rather than leaner exposure.

Two questions remain. First, do distributor suppliers in fact bear port congestion directly, as the channel requires? Second, why are larger focal firms resilient: does their advantage reside in the quality of the suppliers with which they are matched? We address both by examining the supplier side directly. We restrict the sample to distributors that supply focal manufacturers, define an indicator $BigFirmSupplier$ equal to one for distributors that serve exclusively $BigSize$ manufacturers, and interact it with the distributor's own congestion exposure, $JumpDays$. Here, we use distributors' inventory ($INVT_DIS$) rather than their sales as the outcome at this tier because when an inbound shipment is delayed by port congestion, inventory is the first-order margin that actually adjusts at the distributor tier.

Table 5 The Heterogeneity Analysis of Firm Size

VARIABLES	*Sales*			
	BigSize=1		*BigSize*=0	
	(1)	(2)	(3)	(4)
Panel A: OLS				
L.JumpDays	-0.0001	-0.0001	-0.0028	-0.0027
	(0.001)	(0.001)	(0.003)	(0.003)
L.SupplierDays_MFT	-0.0003	0.0000	0.0006	0.0009
	(0.001)	(0.001)	(0.003)	(0.002)
L.SupplierDays_DIS	-0.0001	-0.0001	-0.0102**	-0.0100**
	(0.001)	(0.001)	(0.004)	(0.004)
L.SupplierDays_OTS	0.0022	0.0019	-0.0000	-0.0001
	(0.002)	(0.002)	(0.002)	(0.003)
R-squared	0.909	0.917	0.821	0.822
Observations	7,549	7,456	11,290	11,269
Panel B: IV				
L.SupplierDays_DIS	0.0009	0.0005	-0.0266**	-0.0265**
	(0.002)	(0.002)	(0.013)	(0.013)
KP F Statistics	24.41	25.29	48.30	48.42
Observations	7,549	7,456	11,290	11,269
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Controls		Yes		Yes

Notes: This table shows the heterogenous analysis of focal firms' size. We separate focal firms into two samples according to their firm size in last period. *BigSize* indicates that the firm size of focal manufacturers is above medium. Both OLS and IV results show that firms with smaller firm size suffer more significantly from the propagation of supplier's port congestion shocks. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in columns (2) and (4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 reports the results.[8] In columns (1)–(3), $JumpDays$ enters significantly negatively in the inventory regressions across alternative fixed-effects structures, confirming that congestion measurably draws down distributors' own inventories. In columns (4)–(6), the interaction term is positive and statistically significant: distributors that serve larger manufacturers experience significantly smaller inventory declines when congestion strikes. The results of linear combination between $JumpDays$ and $JumpDays \times BigFirmSupplier$ also show the consistent pattern that the direct impact of port congestion on these distributors is mild. Together, these findings corroborate the two margins of buyer market power. Distributors absorb port shocks directly onto their balance sheets, yet they shield their largest customers from the disruption—whether because large buyers command priority in the rationing of scarce stock or because large buyers self-select into more operationally resilient suppliers ex ante. The resilience of large focal firms documented in Table 5 can thus be traced, at least in part, to their capacity to form relationships with suppliers that are better able to absorb and manage disruption risk, dampening the shock before it propagates downstream.

[8] Because the distributor-supplier sample is small and thinly distributed across industry-by-period cells, adding industry-level fixed effects generates many singleton groups that are dropped from estimation reducing the sample by about one-third. Thus for this tier, we rely on firm, time, and state fixed effects and cluster standard errors at the state level.

Table 6 The Direct Effect of Port Congestion on Distributor Suppliers

VARIABLES	*INVT_DIS*					
	(1)	(2)	(3)	(4)	(5)	(6)
JumpDays	-0.0010**	-0.0010**	-0.0015*	-0.0014***	-0.0013**	-0.0020**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
JumpDays × *BigFirmSupplier*				0.0011**	0.0008*	0.0013**
				(0.000)	(0.000)	(0.001)
Linear Combination: *JumpDays* + *JumpDays* × *BigFirmSupplier*				-0.0003	-0.0005**	-0.0007
				(0.000)	(0.000)	(0.000)
Observations	918	907	835	918	907	835
R-squared	0.967	0.974	0.977	0.967	0.974	0.977
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes			Yes		
Year-Quarter FE	Yes	Yes		Yes	Yes	
Firm-Quarter FE		Yes	Yes		Yes	Yes
State-Year-Quarter FE			Yes			Yes

Notes: This table examines the direct effects of port congestion on distributors that supply downstream manufacturers. The dependent variables is $INVT_DIS$ which is the inventory level of distributors. The independent variables are their own contemporaneous port congestion shocks, *JumpDays*. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before. Based on the size of focal manufacturers, we identify upstream distributors that exclusively serve larger manufacturers in our sample and define an indicator, *BigFirmSupplier*, equal to one for these suppliers. We interact *BigFirmSupplier* with the port congestion measure, *JumpDays*, to investigate whether distributors serving larger customers respond differently to congestion shocks. The results indicate that distributors connected to larger downstream manufacturers maintain significantly higher inventory levels following port congestion shocks, consistent with preferential allocation toward strategically important customers. The linear combinations of *JumpDays* and *JumpDays* × *BigFirmSupplier* in columns (4)-(6) indicate that for those big-firm distributors, the direct impact of port congestion is mild. Robust standard errors clustered at state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2. Inventory Depletion

Consistent with above analysis, the pathway through which an upstream shock reaches the focal firm runs through the depletion of its inventory. Under stochastic and unobservable supplier lead times, standard base-stock inventory theory prescribes that the optimal short-run response to a delivery delay is to draw down existing safety stock to sustain production while waiting for replenishment, rather than to halt operations or incur the cost of expedited substitute sourcing (Song 1994, Kouvelis and Li 2012). When upstream port congestion lengthens and randomizes supplier delivery lead times, the focal firm consumes intermediate inputs faster than it can replace them, so its inventory buffer absorbs the shock first. Once that buffer is exhausted, the constraint binds on production: line schedules slip, and shipments decline. This mechanism implies a sequential signature in which upstream congestion first compresses the focal firm's inventory, and that compression in turn drives the subsequent sales decline.

To test for this signature, we decompose the focal manufacturer's total inventory ($INVT$) into its Compustat components: raw materials ($INVR$), work-in-process ($INVW$), and finished goods ($INVF$), and re-estimate the dynamic OLS specification (Eq. 1) and the 2SLS second stage (Eq. 2) with each of the four inventory measures as the dependent variable. Table 7 reports the estimates, with the OLS results in Panel A and the IV results in Panel B. In Panel A, supplier congestion

(*SupplierDays*) produces statistically significant declines in aggregate inventory, concentrated in raw materials and work-in-process. This pattern traces the supply-chain flow predicted by the mechanism: disruption at the supplier level first creates a raw-material shortage at the focal firm, which then starves the work-in-process stage and ultimately constrains shipments. The 2SLS estimates in Panel B preserve this pattern, confirming that the indirect congestion shock causally compresses the focal firm's inventory rather than merely co-moving with it.

Table 7 The Impact of Port Congestion on Inventory Shortage

VARIABLES	*INVT*	*INVR*	*INVW*	*INVF*
	(1)	(2)	(3)	(4)
Panel A: OLS				
JumpDays	0.0013*	0.0001	-0.0000	0.0013*
	(0.001)	(0.000)	(0.000)	(0.001)
L.JumpDays	0.0003	-0.0002	0.0001	-0.0000
	(0.001)	(0.000)	(0.000)	(0.000)
L2.JumpDays	-0.0005	0.0000	-0.0003	-0.0007
	(0.001)	(0.000)	(0.000)	(0.001)
SupplierDays	-0.0010***	-0.0002	-0.0002*	-0.0005
	(0.000)	(0.000)	(0.000)	(0.000)
L.SupplierDays	-0.0004	-0.0002**	-0.0001	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
L2.SupplierDays	0.0000	-0.0001	-0.0001	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.888	0.934	0.924	0.905
Observations	19,363	16,629	16,485	16,710
Panel B: IV				
L.SupplierDays	-0.0045**	-0.0023**	-0.0019*	-0.0017
	(0.002)	(0.001)	(0.001)	(0.001)
KP F Statistics	48.65	35.03	36.41	46.09
Observations	19,373	16,639	16,495	16,720
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Control	Yes	Yes	Yes	Yes

Notes: This table shows both OLS and IV results of port congestion on different kinds of focal firms' inventory including total inventory (*INVT*), raw material inventory (*INVR*), work-in-process inventory (*INVW*), and finished goods inventory (*INVF*). We include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in all columns. Results show that port congestion shock propagated from domestic suppliers can lead to inventory shortage of focal manufacturers, especially total inventory, raw material inventory, and work-in-process inventory. Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

If propagation operates through buffer depletion, its strength should depend on the firm's pre-shock inventory position. Firms entering a shock with deeper buffers can sustain production through a longer span of disrupted deliveries before the constraint binds, so the shock dissipates inside the inventory account before it reaches the production line; lean firms hit the constraint quickly and translate supplier delay almost directly into missed shipments. Propagation should therefore be attenuated for

firms holding more inventory ahead of the shock. To test this moderation, we interact $SupplierDays$ with the firm's pre-shock inventory position, measured by two-period-lagged total and raw-material inventory ($PreINVT$ and $PreINVR$), and re-estimate Eq. 1.[9] Table 8 reports the results. The interaction coefficient is positive and statistically significant, indicating that firms with higher pre-shock inventory experience smaller sales declines from a given supplier shock. Consistent with the base-stock logic, the inventory buffer absorbs the propagated disruption, and this buffering role echoes prior evidence on inventory as a margin of adjustment to supply-chain risk (Alessandria et al. 2010).

Table 8 The Effect of Inventory Buffer

VARIABLES	*Sales*			
	(1)	(2)	(3)	(4)
L.SupplierDays	-0.0026***	-0.0023***	-0.0011	-0.0007
	(0.001)	(0.001)	(0.001)	(0.001)
L.SupplierDays × *PreINVT*	0.0111***	0.0103**		
	(0.002)	(0.004)		
PreINVT	-0.0781	-0.1086		
	(0.091)	(0.097)		
L.SupplierDays × *PreINVR*			0.0238**	0.0225*
			(0.010)	(0.011)
L.SupplierDays × *PreINVNR*			-0.0046	-0.0054
			(0.008)	(0.009)
PreINVR			0.0296	0.0186
			(0.097)	(0.096)
PreINVNR			-0.1467	-0.1785
			(0.147)	(0.149)
Observations	13,514	13,482	11,108	11,076
R-squared	0.865	0.859	0.884	0.879
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
Quantile FE	Yes		Yes	
Firm Controls		Yes		Yes

Notes: This table shows the effect of inventory buffer under suppliers' shocks. We utilize two-period lagged total inventory level and raw material inventory as the *PreINVT* and *PreINVR* before shocks. We interact previous inventory level with suppliers' port congestion shocks. Also, in columns (3) and (4), we control other types of inventories besides raw materials denoted as *PreINVNR*. Results show that with higher level of total inventory or raw material inventory before shocks, focal manufacturers can better tackle with suppliers' port congestion shocks indicating that inventory can work as a buffer. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in columns (2) and (4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3. Production Capacity

Even among firms exposed to the same propagated shock, the translation of an upstream delay into lost sales depends on the focal firm's operational slack which is its capacity to absorb the delay without interrupting output and to recover lost throughput once supply resumes. Firms operating at high capacity utilization hold no spare production capacity to compensate for missing inputs

[9] We use two-period-lagged inventory to mitigate endogeneity, as the impact of a congestion shock persists for roughly two periods in our estimates.

or to catch up on deferred output after deliveries normalize, so a given input delay maps more directly into permanent sales losses. Firms running below capacity, by contrast, can ramp output once supply resumes and recover the throughput forgone during the disruption. Higher capacity utilization therefore amplifies propagation by tightening the focal firm's margin of adjustment.

To examine this channel, we proxy capacity utilization by the ratio of sales to net property, plant, and equipment ($Sales/PPENT$) in 2016, which we denote $CapacityUtilize$; higher values indicate tighter capacity and less operational slack (Hendricks et al. 2009). We interact $CapacityUtilize$ with the direct and indirect congestion measures and re-estimate both the dynamic OLS specification (Eq. 1) and the 2SLS second stage (Eq. 2). Table 9 reports the estimates, with OLS in Panel A and IV in Panel B. The interaction term $L.SupplierDays \times L.CapacityUtilize$ is negative and statistically significant in both panels. Firms operating at higher capacity utilization, those with the least slack, thus suffer larger sales losses from a given supplier shock, because they cannot make up the missing production once supply resumes. This evidence indicates that limited production capacity amplifies the downstream propagation of upstream congestion shocks.

6. Heterogeneity Analysis

We now examine two dimensions of cross-sectional heterogeneity that sharpen the mechanism evidence developed above: the specificity of the disrupted inputs and the time sensitivity of the focal firm's products. Both dimensions govern how readily an upstream delay is converted into a downstream production loss, and each predicts where the propagation of supplier congestion should be most acute.

6.1. Input Specificity

The propagation of a supplier shock depends critically on whether the focal firm can substitute around the congested supplier. When the disrupted inputs are commoditized and multi-sourced, the focal firm can rebalance its orders toward unaffected suppliers, slowing the rate at which its inventory buffer depletes and cushioning production. When the inputs are relationship-specific, technologically customized, or designed-in, however, the firm cannot re-source across suppliers on short notice (Barrot and Sauvagnat 2016). In that case, the buffer is consumed without replenishment, and a given delay translates into a disproportionate production loss. Input specificity should therefore amplify the propagation of supplier shocks precisely by removing the substitution margin that would otherwise absorb the inventory drawdown.

To test this, we proxy input specificity by industry-level contract intensity (*ContractIntensity*), following Nunn (2007): industries that rely more heavily on relationship-specific investments require greater contractual safeguards, so higher contract intensity reflects greater input specificity. Building on Eq. 1 and Eq. 2, we add interactions between the congestion measures and *ContractIntensity*.

Table 9 The Channel of Production Capacity

VARIABLES	*Sales*			
	(1)	(2)	(3)	(4)
Panel A: OLS				
L.JumpDays	-0.0005	-0.0011	-0.0008	-0.0011
	(0.001)	(0.001)	(0.001)	(0.001)
L.SupplierDays	0.0000	-0.0000	0.0001	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
L.JumpDays × *CapacityUtilize*	-0.0008	-0.0009	-0.0010*	-0.0010
	(0.000)	(0.000)	(0.000)	(0.000)
L.SupplierDays × *CapacityUtilize*	-0.0001***	-0.0001***	-0.0001***	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.830	0.835	0.845	0.836
Observations	18,924	18,876	18,852	18,711
Panel B: IV				
L.SupplierDays	-0.0056	-0.0074*	-0.0072	-0.0073*
	(0.005)	(0.004)	(0.004)	(0.004)
L.SupplierDays × *CapacityUtilize*	-0.0002***	-0.0002***	-0.0001***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
KP F Statistics	23.88	24.71	24.47	24.83
Observations	18,924	18,876	18,852	18,711
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE		Yes	Yes	Yes
Quantile FE			Yes	
Firm Control				Yes

Notes: This table examines whether focal firms with less operational slack suffer more from supplier port-congestion shocks. *CapacityUtilize* proxies the focal firm's capacity utilization by the ratio of sales to net property, plant, and equipment (Sales/PPENT); higher values indicate tighter capacity and less room to catch up on deferred output once supply resumes. We interact *CapacityUtilize* with the congestion measures. Both OLS (Panel A) and IV (Panel B) show that the interaction *L.SupplierDays* × *L.CapacityUtilize* is negative and significant, indicating that firms operating at higher capacity utilization suffer more from supplier shocks because they cannot make up the missing production. The same lagged firm-level controls (*Size*, *ROA*, *Lev*) as before are included in column (4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10 reports the results, with Panel A presenting the OLS estimates and Panel B the 2SLS estimates. In both panels, the coefficient on *L.SupplierDays* × *ContractIntensity* is negative and statistically significant: manufacturers in higher-contract-intensity, and thus more input-specific, industries suffer significantly greater sales losses from supplier shocks. Because specific inputs cannot be quickly re-sourced when an upstream supplier is congested, the rigidity of these inputs amplifies the damage propagated by upstream logistical failures.

6.2. Time Sensitivity

A parallel logic applies to the temporal slack embedded in the focal firm's operations. Firms in time-sensitive industries characterized by short product life cycles, perishable goods, just-in-time scheduling, or high inventory turnover structure their operations to minimize buffer stock as a competitive necessity. This leaves little temporal slack with which to absorb an upstream delay, so that

Table 10 The Heterogeneity Analysis of Input Specificity

VARIABLES	*Sales*			
	(1)	(2)	(3)	(4)
Panel A: OLS				
L.JumpDays	0.0001	-0.0020	-0.0003	-0.0016
	(0.004)	(0.005)	(0.004)	(0.004)
L.SupplierDays	0.0044	0.0045*	0.0034	0.0044*
	(0.003)	(0.002)	(0.002)	(0.002)
L.JumpDays × *ContractIntensity*	0.0006	0.0024	0.0008	0.0016
	(0.006)	(0.007)	(0.006)	(0.007)
L.SupplierDays × *ContractIntensity*	-0.0083**	-0.0084***	-0.0068**	-0.0082***
	(0.004)	(0.003)	(0.003)	(0.003)
R-squared	0.820	0.828	0.832	0.832
Observations	12,039	11,990	11,868	11,852
Panel B: IV				
L.SupplierDays	0.0240	0.0222	0.0204	0.0215
	(0.017)	(0.017)	(0.016)	(0.017)
L.SupplierDays × *ContractIntensity*	-0.0484**	-0.0487*	-0.0447*	-0.0468*
	(0.024)	(0.024)	(0.023)	(0.025)
KP F Statistics	16.47	18.69	17.88	19.51
Observations	12,039	11,990	11,973	11,868
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE		Yes	Yes	Yes
Quantile FE			Yes	
Firm Control				Yes

Notes: This table shows the heterogeneity analysis of input specificity. Following Nunn (2007), we use industrial contract intensity as a proxy for input or relationship specificity, denoted as *ContractIntensity*. With higher relationship specificity or input specificity, the contract intensity should be higher for greater contract enforcement. We interact *ContractIntensity* with *SupplierDays* and include it in the regression. Both OLS and IV results show that manufacturers in industries with relatively higher contract intensity are affected more prominently by suppliers' shocks. If focal firms require input-specific goods from suppliers, supplier shocks would lead to greater impact on focal firms' sales. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in the column (4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

even modest disruptions translate quickly into stockouts and lost orders. The propagation of supplier congestion should therefore be concentrated among time-sensitive focal firms, while firms with greater temporal slack should be largely insulated.

Following Djankov et al. (2010), we classify focal firms into time-sensitive and non-time-sensitive industries, with details reported in Appendix Table A2.[10,11] We then re-estimate Eq. 1 and Eq. 2 separately by subgroup.

Table 11 reports the results. The negative effect of supplier shocks is concentrated entirely in time-sensitive industries and is statistically insignificant for time-insensitive firms. This pattern is

[10]The time-sensitive manufacturing industries are those with the highest willingness to pay for air freight in Hummels and Schaur (2013), while time-sensitive agricultural products are fruits and vegetables with a post-harvest storage life of three weeks or less.

[11]Based on Djankov et al. (2010), we convert their lists, which are classified by HS and SITC code, into SIC codes; after merging into our dataset via SIC, we classify the sample into two comparison groups using SIC three-digit codes.

consistent with our argument: firms in time-sensitive sectors operate with minimal inventory slack, so a delayed delivery from a domestic supplier passes through quickly to lost output, whereas firms with more temporal slack can absorb the same delay. As a robustness check, Table A3 re-estimates the subgroup specifications using the alternative time-insensitive classification of Djankov et al. (2010) and yields a consistent pattern.

Table 11 The Heterogeneity Analysis of Time Sensitivity

VARIABLES	*Sales*			
	Sensitive=1		*Sensitive*=0	
	(1)	(2)	(3)	(4)
Panel A: OLS				
JumpDays	-0.0019	-0.0020	0.0008	0.0008
	(0.001)	(0.001)	(0.001)	(0.001)
L.JumpDays	-0.0016	-0.0018	-0.0007	-0.0009
	(0.002)	(0.002)	(0.001)	(0.001)
L2.JumpDays	-0.0009	-0.0011	-0.0012	-0.0012
	(0.003)	(0.003)	(0.001)	(0.001)
SupplierDays	-0.0031*	-0.0034	-0.0005	-0.0005
	(0.002)	(0.002)	(0.001)	(0.001)
L.SupplierDays	-0.0045***	-0.0043***	-0.0005	-0.0004
	(0.000)	(0.001)	(0.001)	(0.001)
L2.SupplierDays	-0.0014	-0.0011	-0.0001	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.804	0.801	0.827	0.830
Observations	4,921	4,853	14,709	14,446
Panel B: IV				
L.SupplierDays	-0.0300***	-0.0301***	-0.0029	-0.0028
	(0.001)	(0.002)	(0.006)	(0.006)
KP F Statistics	86.40	81.98	32.96	33.17
Observations	4,921	4,853	14,719	14,456
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Control		Yes		Yes

Notes: This table shows the heterogenous analysis of time sensitivity. We classify focal firms into two comparing groups according to Djankov et al. (2010) which provides lists of time-sensitive and time-insensitive industries and products (details in appendix). We convert above lists into SIC industry level. Accordingly, *Sensitive*=1 indicates that focal firms' industries are relatively more time-sensitive compared to *Sensitive*=0. Both OLS and IV results show that manufacturers in industries with relatively higher time sensitivity are affected more prominently by suppliers' shocks. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in columns (2)(4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7. Conclusion Remarks

This paper studies how transportation bottlenecks propagate through supply chain networks and affect downstream firm performance. Using high-frequency AIS vessel-tracking data, we construct a novel port-level congestion measure and combine it with detailed supply chain relationships from Panjiva and FactSet Revere. This integrated dataset allows us to trace congestion shocks from ports to

importing suppliers and further to downstream domestic firms. Exploiting exogenous variation in port congestion induced by wind conditions, we provide causal evidence on how disruptions originating in international shipping transmit through domestic supply chains.

Our central finding is an asymmetry between indirect and direct exposure. Indirect exposure to port congestion through domestic suppliers (*SupplierDays*) has a substantially larger impact on firm performance than firms' own direct exposure (*JumpDays*), whose effect is economically small and statistically insignificant. While importing firms appear able to absorb port congestion through buffering mechanisms, congestion faced by upstream suppliers generates economically meaningful declines in downstream sales. This result highlights the presence of pronounced ripple effects and demonstrates that transportation disruptions propagate beyond firms directly engaged in international trade.

We then unpack the transmission through three mechanisms. First, the propagation operates through supplier type and is shaped by focal-firm size: the indirect effect is concentrated in distributor suppliers, reflecting their central coordinating role and their lack of production flexibility and per-SKU inventory depth, whereas shocks at manufacturer suppliers transmit little, mirroring the weak direct effect; larger focal firms, in turn, exhibit greater resilience, consistent with priority allocation during disruptions and more resilient supplier relationships secured ex ante. Second, the propagation works through inventory depletion: supplier-level congestion leads to significant reductions in downstream firms' raw material and work-in-process inventories, impairing their ability to sustain production and meet demand, while firms entering the shock with greater pre-shock inventory buffers are better able to mitigate these effects, underscoring the role of inventory as an intertemporal buffer against upstream disruptions. Third, the propagation depends on production capacity: firms operating at high capacity utilization have little spare capacity to compensate for missing inputs or to recover deferred output once supply resumes, and therefore suffer larger sales losses. Beyond these mechanisms, we document heterogeneity along two dimensions: the effects are amplified for focal firms whose inputs are more relationship-specific, and for firms in more time-sensitive industries where delays are more costly and less easily absorbed.

Taken together, these results trace a coherent theoretical framework, which we summarize in Figure 5. Port congestion originating with foreign suppliers reaches focal U.S. manufacturers along two paths. The direct path via the focal firm's own port exposure (*JumpDays*) is muted, because importing manufacturers absorb their own port-side disruptions through contractual flexibility and buffer inventories of imported intermediates. The indirect path runs through domestic suppliers (*SupplierDays*): a port disruption at an importing domestic supplier is, in effect, an international logistics shock transmitted one node downstream. This indirect shock is compiled at the supplier tier and is concentrated among distributors, who possess neither production flexibility nor deep per-SKU inventory and thus convert an inbound shortfall almost immediately into a stockout against the

next downstream order. The shock then reaches focal-firm sales through the channels of inventory depletion and production capacity, and its strength is governed by the focal firm's market power. The transmission is further moderated by input specificity and time sensitivity, which determine how much of a given upstream delay maps into lost output. Figure 5 lays out these paths and channels.

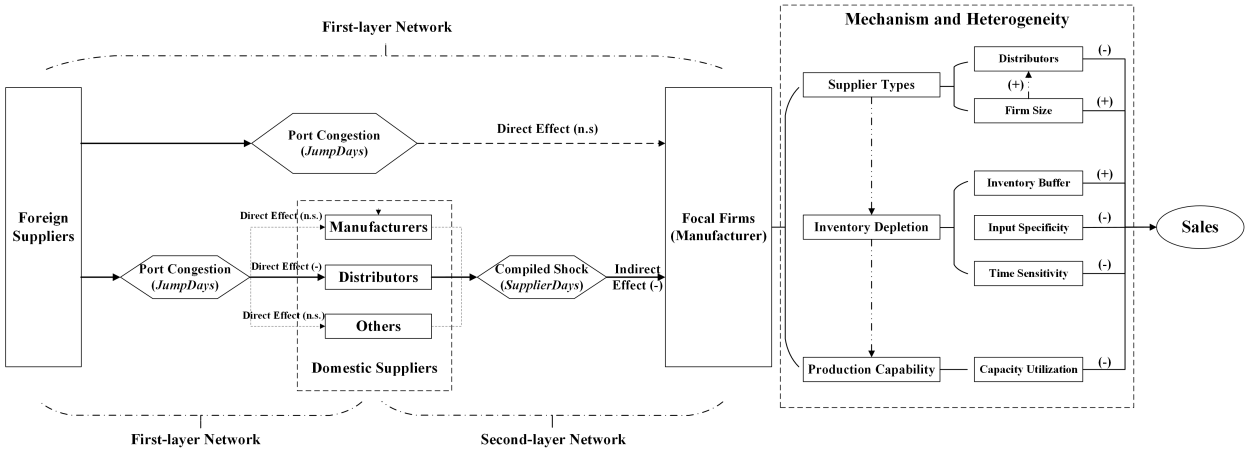


Figure 5 The Theoretical Framework

Note: This figure summarizes the theoretical framework of the paper. Foreign-supplier port congestion reaches focal U.S. manufacturers both directly (*JumpDays*, an insignificant effect) and indirectly through domestic suppliers (*SupplierDays*). The indirect effect is concentrated in distributor suppliers and is transmitted to focal-firm sales through the channels of inventory depletion, production capacity, and is shaped by input specificity, time sensitivity, and focal-firm market power. "n.s." indicates not significant.

Collectively, these findings contribute to the operations management literature in several ways. First, we extend the growing literature on shock propagation in production networks by providing micro-level causal evidence on transportation-induced disruptions, showing that logistics frictions, not only physical disasters or financial distress, travel downstream through domestic tiers. Second, we contribute to the literature on global sourcing by challenging the conventional view that domestic sourcing is inherently safer than foreign sourcing: under modern, interconnected supply chains, domestic tiers can embed substantial exposure to global transportation shocks, because the focal firm has not buffered against a risk it does not perceive itself to bear. Third, methodologically, we introduce a novel, high-frequency port congestion measure and demonstrate how it can be combined with supply chain network data to study disruption transmission.

Our findings also offer several managerial implications. The results emphasize that supply chain risk management should extend beyond a firm's own logistics operations to include upstream domestic suppliers, since reliance on domestic sourcing alone does not insulate firms from global transportation disruptions when suppliers themselves depend on imported inputs. Managers should therefore

monitor suppliers' exposure to logistics bottlenecks paying particular attention to distributor suppliers, who transmit shocks most forcefully, and incorporate such risks into sourcing and inventory decisions. Maintaining adequate safety stock, especially for relationship-specific inputs, can serve as an effective buffer against propagated disruptions, while firms operating at high capacity utilization or in time-sensitive industries have the least slack to absorb upstream delay and stand to benefit most from enhanced visibility into suppliers' inventory positions and delivery reliability, as well as from contingency planning that accounts for upstream transportation risks.

Overall, this study highlights the importance of viewing supply chains as interconnected networks in which transportation shocks can propagate across organizational and geographic boundaries. As global supply chains continue to face heightened uncertainty, understanding and managing these propagation mechanisms will be essential for building more resilient production systems.

References

Acemoglu D, Tahbaz-Salehi A (2025) The macroeconomics of supply chain disruptions. *Review of Economic Studies* 92(2):656–695.

Agca S, Babich V, Birge JR, Wu J (2022) Credit shock propagation along supply chains: Evidence from the cds market. *Management Science* 68(9):6506–6538.

Alessandria G, Kaboski JP, Midrigan V (2010) Inventories, lumpy trade, and large devaluations. *American Economic Review* 100(5):2304–2339.

Alessandria G, Kaboski JP, Midrigan V (2011) Us trade and inventory dynamics. *American Economic Review* 101(3):303–307.

Alessandria G, Khan SY, Khederlarian A, Mix C, Ruhl KJ (2023) The aggregate effects of global and local supply chain disruptions: 2020–2022. *Journal of International Economics* 146:103788.

Arrow KJ, Harris T, Marschak J (1951) Optimal inventory policy. *Econometrica: Journal of the Econometric Society* 250–272.

Bai X, Fernández-Villaverde J, Li Y, Zanetti F (2024) The causal effects of global supply chain disruptions on macroeconomic outcomes: evidence and theory. *NBER Working Paper* (w32098).

Barrot JN, Sauvagnat J (2016) Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics* 131(3):1543–1592.

Bernard AB, Jensen JB, Redding SJ, Schott PK (2010) Wholesalers and retailers in us trade. *American Economic Review* 100(2):408–413.

Bloom N (2009) The impact of uncertainty shocks. *Econometrica* 77(3):623–685.

Boehm CE, Flaaen A, Pandalai-Nayar N (2019) Input linkages and the transmission of shocks: Firm-level evidence from the 2011 tōhoku earthquake. *Review of Economics and Statistics* 101(1):60–75.

Brancaccio G, Kalouptsidi M, Papageorgiou T (2025) Rigidities in transportation and supply chain disruptions. *AEA Papers and Proceedings* 115:543–550.

Card D (2001) Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica* 69(5):1127–1160.

Carvalho VM, Nirei M, Saito YU, Tahbaz-Salehi A (2021) Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics* 136(2):1255–1321.

Charoenwong B, Han M, Wu J (2023) Trade and foreign economic policy uncertainty in supply chain networks: who comes home? *Manufacturing & Service Operations Management* 25(1):126–147.

Ding H, Hu Y, Jiang H, Wu J, Zhang Y (2023) Social embeddedness and supply chains: Doing business with friends versus making friends in business. *Production and Operations Management* 32(7):2154–2172.

Ding H, Huang D, Wu J (2026) Hurricane disruption costs in global supply chains: Lead time uncertainty and the value of visibility. *Available at SSRN* .

Djankov S, Freund C, Pham CS (2010) Trading on time. *The Review of Economics and Statistics* 92(1):166–173.

Esposito F, Heise S, Blaum J (2024) Input sourcing under climate risk: Evidence from us manufacturing firms. *Available at SSRN 5127342* .

Fisher ML (1997) What is the right supply chain for your product? *Harvard Business Review* 75:105–117.

Fransoo JC, Lee CY (2013) The critical role of ocean container transport in global supply chain performance. *Production and Operations Management* 22(2):253–268.

Ganapati S (2025) The modern wholesaler: Global sourcing, domestic distribution, and scale economies. *American Economic Journal: Microeconomics* 17(1):1–40.

Grossman GM, Helpman E, Lhuillier H (2023) Supply chain resilience: Should policy promote international diversification or reshoring? *Journal of Political Economy* 131(12):3462–3496.

Heij C, Knapp S (2015) Effects of wind strength and wave height on ship incident risk: regional trends and seasonality. *Transportation Research Part D: Transport and Environment* 37:29–39.

Hendricks KB, Singhal VR, Zhang R (2009) The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of operations management* 27(3):233–246.

Hummels DL, Schaur G (2013) Time as a trade barrier. *American Economic Review* 103(7):2935–2959.

Jain N, Girotra K, Netessine S (2022) Recovering global supply chains from sourcing interruptions: The role of sourcing strategy. *Manufacturing & Service Operations Management* 24(2):846–863.

Jain N, Wu D (2023) Can global sourcing strategy predict stock returns? *Manufacturing & Service Operations Management* 25(4):1357–1375.

Kesavan S, Kushwaha T, Gaur V (2016) Do high and low inventory turnover retailers respond differently to demand shocks? *Manufacturing & Service Operations Management* 18(2):198–215.

Khan SY, Khederlarian A (2025) Inventories, input costs, and productivity gains from trade liberalizations. *International Economic Review* 66(1):175–199.

Kouvelis P, Li J (2012) Contingency strategies in managing supply systems with uncertain lead-times. *Production and Operations Management* 21(1):161–176.

Lafrogne-Joussier R, Martin J, Mejean I (2022) Supply shocks in supply chains: Evidence from the early lockdown in china. *IMF Economic Review* 71(1):170.

Niu Y, Werle N, Cohen M, Cui S, Deshpande V, Ernst R, Huchzermeier A, Tsay AA, Wu J (2025) Restructuring global supply chains: Navigating challenges of the covid-19 pandemic and beyond. *Manufacturing & Service Operations Management* .

Nunn N (2007) Relationship-specificity, incomplete contracts, and the pattern of trade. *The Quarterly Journal of Economics* 122(2):569–600.

Pankratz NM, Schiller CM (2024) Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies* 37(6):1729–1777.

Song JS (1994) The effect of leadtime uncertainty in a simple stochastic inventory model. *Management Science* 40(5):603–613.

Spulber DF (1996) Market microstructure and intermediation. *Journal of Economic Perspectives* 10(3):135–152.

Verschuur J, Koks EE, Hall JW (2023) Systemic risks from climate-related disruptions at ports. *Nature Climate Change* 13(8):804–806.

Wang Y, Li J, Wu D, Anupindi R (2021) When ignorance is not bliss: An empirical analysis of subtier supply network structure on firm risk. *Management Science* 67(4):2029–2048.

Appendix

Appendix A. Variable Definitions and Data Sources

Table A1: The Definition and Data Sources of Variables

Variable	Definition	Source
Dependent Variables		
Sales	quarterly sales / total assets at same quarter in last year	Compustat
INVT	total inventory / total assets at same quarter in last year	Compustat
INVR	inventory of raw materials / total assets at same quarter in last year	Compustat
INVF	inventory of finished goods / total assets at same quarter in last year	Compustat
INVW	inventory of working in process / total assets at same quarter in last year	Compustat
Independent Variables		
JumpDays	the quarterly unique affected days of jump events indicating port congestion	AIS & Panjiva
SupplierDays	the quarterly unique affected days of suppliers' *JumpDays*	AIS & Panjiva & FactSet
SupplierWindDays	the quarterly unique affected days of suppliers' jump events from maximum wind speed	ERA5 & Panjiva & FactSet
SupplierDays_MFT	the quarterly unique affected days of manufacturing suppliers' *JumpDays*	AIS & Panjiva & FactSet & Compustat
SupplierDays_DIS	the quarterly unique affected days of distributor suppliers' *JumpDays*	AIS & Panjiva & FactSet & Compustat
SupplierDays_OTS	the quarterly unique affected days of other suppliers' *JumpDays*	AIS & Panjiva & FactSet & Compustat
JumpSum	the quarterly total affected times of jump events indicating port congestion	AIS & Panjiva
SupplierSum	the quarterly total affected times of suppliers' *JumpSum*	AIS & Panjiva & FactSet
Control Variables		
Size	log(total assets)	Compustat
ROA	net income / total assets	Compustat
Lev	total liabilities / total assets	Compustat
Other Variables		
PreINVT	*INVT* in two periods before	Compustat
PreINVR	*INVR* in two periods before	Compustat
PreINVNR	other aggregated inventory except *INVR* in two periods before	Compustat
CapacityUtilize	sales / net property, plant, and equipment (in 2016)	Compustat
ContractIntensity	proxy for input or relationship specificity at industrial level	Nunn (2007)
Sensitive	dummy indicating time-sensitive industries	Djankov et al. (2010)
Insensitive	dummy indicating time-insensitive industries	Djankov et al. (2010)
BigSize	dummy indicating firms with larger firm size above median	Compustat

Notes: This table shows the detailed definition and data source of each variable in this paper.

Appendix B. Illustration of Port Congestion and Wind Shocks

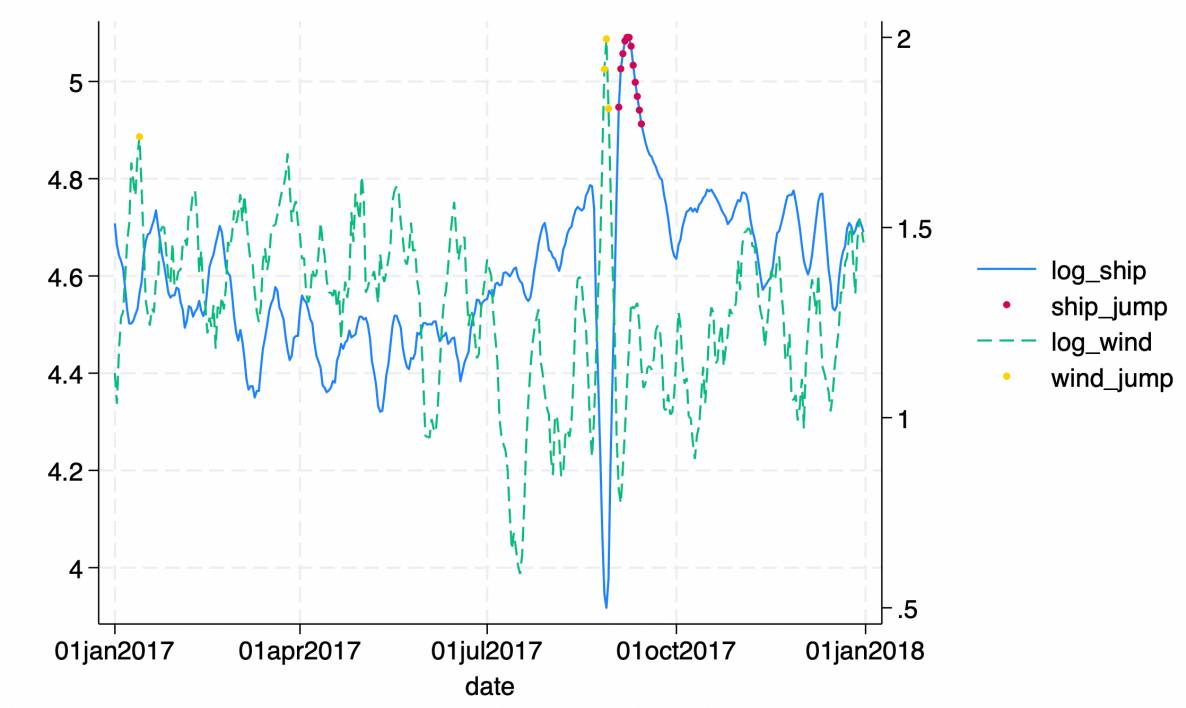


Figure A1 Port Congestion and Extreme Wind Speed at the Port of Houston in 2017

Note: This figure shows the port congestion and extreme wind speed in Port of Houston in 2017. The blue line shows the logarithm value of daily shipment flows with one-week moving average calculated via AIS data. Red dots indicate jump events identified by Bloom (2009)'s method. The green line shows the logarithm value of daily maximum wind speed with one-week moving average from ERA5 database. Yellow dots indicate jump events of extreme wind speed using the same identification method as above. This figure suggests that the Port of Houston has suffered a significant port congestion shock in August and September 2017 following with the extreme wind speed shocks (Hurricane Harvey in reality).

Appendix C. Classification of Time-Sensitive Industries

Table A2 The Classification of Time-sensitive and Time-insensitive Industries

Time-Sensitive		Time-Insensitive	
SIC	**Industry Description**	**SIC**	**Industry Description**
3579	Office Machines, Nec	2299	Textile Goods, Nec
3571	Electronic Computers	2211	Broadwoven Fabric Mills, Cotton
3577	Computer Peripheral Equipment, Nec	2221	Broadwoven Fabric Mills, Manmade
3621	Motors and Generators	2299	Textile Goods, Nec
3679	Electronic Components, Nec	2259	Knitting Mills, Nec
3612	Power, Distribution and Specialty Transformers	2399	Fabricated Textile Products, Nec
3845	Electromedical Equipment	2295	Coated Fabrics, Not Rubberized
3631	Household Cooking Equipment	2296	Tire Cord and Fabrics
3671	Electron Tubes	2297	Nonwoven Fabrics
3699	Electrical Equipment and Supplies, Nec	23	Apparel, Finished Prdcts from Fabrics & Similar Materials
3861	Photographic Equipment and Supplies	3253	Ceramic Wall and Floor Tile
3861	Photographic Equipment and Supplies	3274	Lime
3861	Photographic Equipment and Supplies	3241	Cement, Hydraulic
3827	Optical Instruments and Lenses	3259	Structural Clay Products, Nec
3873	Watches, Clocks, Watchcases, and Parts	33	Primary Metal Industries
		34	Fabricated Metal Prdcts, Except Machinery & Transport Eqpmnt
		3211	Flat Glass
		3221	Glass Containers
		3269	Pottery Products, Nec
		25	Furniture and Fixtures

Notes: This table shows the classification of time sensitivity according to Djankov et al. (2010). Djankov et al. (2010) provides lists of time-sensitive and time-insensitive industries and products. We convert lists into SIC industry level and use SIC three-digit in our regression.

Table A3 Robustness of Time Sensitivity Analysis

VARIABLES	*Sales*			
	Insensitive=1		*Insensitive*=0	
	(1)	(2)	(3)	(4)
Panel A: OLS				
JumpDays	0.0001	-0.0006	0.0003	0.0004
	(0.004)	(0.004)	(0.001)	(0.001)
L.JumpDays	-0.0009	0.0006	-0.0004	-0.0005
	(0.004)	(0.004)	(0.001)	(0.001)
L2.JumpDays	-0.0087	-0.0046	-0.0003	-0.0004
	(0.007)	(0.004)	(0.001)	(0.001)
SupplierDays	-0.0036*	-0.0031*	-0.0010*	-0.0011**
	(0.002)	(0.002)	(0.001)	(0.001)
L.SupplierDays	-0.0000	0.0009	-0.0014***	-0.0012**
	(0.002)	(0.001)	(0.000)	(0.001)
L2.SupplierDays	0.0005	0.0023	-0.0006	-0.0005
	(0.006)	(0.003)	(0.001)	(0.000)
R-squared	0.804	0.848	0.820	0.823
Observations	1,340	1,328	18,298	17,984
Panel B: IV				
L.SupplierDays	0.0017	0.0016	-0.0101**	-0.0098**
	(0.008)	(0.006)	(0.005)	(0.005)
KP F Statistics	20.46	20.14	48.28	48.97
Observations	1,340	1,328	18,308	17,994
Firm-Quarter FE	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes
State-Year-Quarter FE	Yes	Yes	Yes	Yes
Firm Control		Yes		Yes

Notes: This table shows the robustness of time sensitivity analysis for Table 11. We classify focal firms into two comparing groups according to time-insensitive industries and products from Djankov et al. (2010). Accordingly, *Insensitive*=1 indicates that focal firms' industries are relatively more time-insensitive compared to *Insensitive*=0. Both OLS and IV results show that manufacturers in industries with relatively higher time sensitivity are affected more prominently by suppliers' shocks. We also include same lagged firm level time-varying control variables, *Size*, *ROA*, and *Lev* as before in columns (2)(4). Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D. Robustness Checks

Table A4 The Robustness Analysis of Different Thresholds

VARIABLES	*Sales*							
	OLS				*IV*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.JumpDays2	0.0001	-0.0004	-0.0001	-0.0005	-0.0039***	-0.0039***		
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)		
L.SupplierDays2	-0.0007	-0.0007*	-0.0007**	-0.0007*			-0.0033**	-0.0033**
	(0.000)	(0.000)	(0.000)	(0.000)			(0.002)	(0.002)
L.Size				0.0091		0.0091		0.0091
				(0.011)		(0.011)		(0.011)
L.Lev				0.0019*		0.0019*		0.0019*
				(0.001)		(0.001)		(0.001)
L.ROA				0.0130***		0.0130***		0.0129***
				(0.004)		(0.004)		(0.004)
Observations	19,834	19,786	19,744	19,457	19,786	19,457	19,786	19,457
R-squared	0.817	0.821	0.832	0.824				
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Quarter FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quantile FE			Yes					
Firm Controls				Yes		Yes		Yes
KP F Statistics					42.47	42.62	277.9	287.5

Notes: This table shows the robustness by using different thresholds of port congestion shock. Aligned with Bloom (2009), we calculate the unique days of jump events using the 1.65 standard deviation (above the 90% confidence interval), denoted as *JumpDays2* and *SupplierDays2*. Both OLS and IV results show the consistent evidence that port congestion shocks from domestic suppliers can propagate via supply chains to downstream manufacturers. Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5 The Robustness Analysis of Port Congestion Measurement

VARIABLES	*Sales*							
	OLS					*IV*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.JumpSum	-0.0003*	-0.0005**	-0.0003*	-0.0005*	-0.0099	-0.0100		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)		
L.SupplierSum	-0.0001**	-0.0001**	-0.0001*	-0.0000**			-0.0013*	-0.0013*
	(0.000)	(0.000)	(0.000)	(0.000)			(0.001)	(0.001)
L.Size				0.0091		0.0092		0.0090
				(0.011)		(0.011)		(0.016)
L.Lev				0.0019*		0.0019*		0.0019*
				(0.001)		(0.001)		(0.001)
L.ROA				0.0130***		0.0129***		0.0129***
				(0.004)		(0.004)		(0.004)
Observations	19,834	19,786	19,744	19,457	19,786	19,457	19,786	19,457
R-squared	0.817	0.821	0.832	0.824				
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year-Quarter FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quantile FE			Yes					
Firm Controls				Yes		Yes		Yes
KP F Statistics					1.935	1.933	18.57	19.06

Notes: This table shows the robustness by using different measure of port congestion shock. We calculate the total number of jump events instead of unique days, denoted as *JumpSum* and *SupplierSum*. Both OLS and IV results show the consistent evidence that port congestion shocks from domestic suppliers can propagate via supply chains to downstream manufacturers. Robust standard errors clustered at industry and state level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.