Supply Chain Disruptions and Supplier Capital in U.S. Firms

Ernest Liu* Yukun Liu† Vladimir Smirnyagin‡ Aleh Tsyvinski§

Princeton Rochester UVA Yale

December 2, 2024

Abstract

We study the impact of supply chain disruptions on U.S. firms based on the universe of seaborne shipment-level import transactions from 2013 to 2023. The granularity of the data allows us to build an index of firm-level disruptions of international suppliers and introduce a comprehensive set of stylized facts for supply chain relationships in the cross-section of firms. We build a general equilibrium heterogeneous firms model with two types of capital—physical and international supplier capital. Accumulation of supplier capital is an important endogenous margin of adjustment, and limiting this ability substantially delays recovery, especially in financially constrained firms.

Keywords: Supply chain disruptions, Supplier capital, Investment, Firm dynamics

*Department of Economics, Princeton University, Princeton, NJ 08544, U.S.A. Phone: (+1) 609-258-0770. Email: ernestliu@princeton.edu.

†Simon Business School, University of Rochester, Rochester, NY, 14602, U.S.A.

‡Department of Economics, University of Virginia, Charlottesville, VA 22911, U.S.A.

§Department of Economics, Yale University, New Haven, CT 06520, U.S.A.

1 Introduction

Over the last several years, there has been a notable increase in supply chain disruptions, making it a critical concern for policymakers in the U.S. and worldwide. This has been evidenced by recent initiatives aimed at securing supply chains (White House, 2022, 2023). In this paper, we study the impact of supply chain disruptions on U.S. businesses both empirically and quantitatively.

Our first contribution is to build a detailed, high-frequency supply chain disruption index that measures the disruptions of international suppliers exposed by each firm based on granular, nearly real-time data on U.S. seaborne imports.[1] Specifically, our index measures the fraction of established trade pairs that are temporarily inactive and is based on nearly 200 million individual observations of shipment-level supplier-importer relationships. We subsequently merge our firm-level index with the Compustat sample of U.S. listed firms to jointly study supply chain disruptions and various measures of firm performance.

Our firm-level index reveals considerable heterogeneity in the levels and persistence of supply disruptions across U.S. public firms. Between 2020 and 2023, there has been not only a substantial increase in disruptions of international suppliers in the aggregate but also a pronounced widening in the distribution of supply chain disruptions. Specifically, we find that the interdecile range in the severity of disruptions has doubled since 2020 as compared to historical levels. Importantly, while the prevalence of supply chain disruptions has subsided between 2021 and 2023, the cross-sectional dispersion has persisted, indicating ongoing pressures on supply chains that firms continue to experience.

[1]This index has a two-week latency and is updated monthly at the www.disruptions.supply for the product, U.S. region and country-of-origin levels. The additional details are in the technical report (Liu, Smirnyagin and Tsyvinski, 2023).

Consistent with our definition of a supply chain disruption, we measure firm-level supplier capital as the total import value accounted for by established trade partners. Given the nature of the data we use (seaborne U.S. imports), this metric specifically represents international supplier capital. We document and report several empirical facts about supplier capital and supply chain disruptions.

First, the distribution of firms with respect to supplier capital is highly right-skewed. While a typical firm imports approximately 3.5 million USD worth of products from established trade partners per quarter, firms in the 10^{th} and 90^{th} percentiles import 0.18 million USD and 54 million USD, respectively. Furthermore, the distribution of supplier capital growth rates—which we interpret as rates of investment into supplier capital—is highly dispersed in the cross-section, roughly five times more dispersed than the distribution of physical capital investment rates.

Second, we observe that firms tend to increase their investment in supplier capital upon receiving a supply disruption shock. However, this response exhibits pronounced heterogeneity: more leveraged firms increase investment in supplier capital by less following such a shock. In contrast, investment in physical capital declines in response to a supply disruption shock, though this effect is both economically and statistically less significant.

Third, we find that supply chain disruptions are associated with lower stock returns and revenue. Financial conditions play an important role, as stock returns and revenue decline more significantly for financially distressed firms. We consider three common measures of financial constraints—the long-term debt ratio, the Whited and Wu (2006) measure, and the Kaplan and Zingales (1997) measure—and find consistent results across all these metrics.

We also explore critical supply chains. We measure how critical a given product category is based on supplier concentration. The underlying assumption is that products with a smaller, more concentrated supplier base increase vulnerability to disruptions, while a diverse supplier base offers greater flexibility. We find that the group of firms with a high share of critical imports exhibited similar exposure to supply chain disruptions over the last decade compared to the group with a low share. However, the "high share" group experienced a spike in supply chain pressures in mid-2020 that was nearly twice the size of what the "low share" group experienced. We interpret these results as evidence supporting policymakers' efforts to improve the resilience of supply chains, with a particular focus on critical supply chains. The data indicates that firms with high dependence on critical products experience a much larger increase in supply chain disruptions during adverse aggregate economic conditions.

Building on our detailed empirical analysis of supply chain disruptions, we develop a general equilibrium model with heterogeneous firms wherein firms invest in two types of capital—physical capital and supplier capital. Firms operate subject to idiosyncratic, persistent productivity shocks, which result in a cross-sectional distribution of firms. Investment in both capital stocks is subject to adjustment costs, the prevalence of which we parameterize using data on the dispersion of investment rates. Every time period, some fraction of firms receives a supply disruption shock in which case a portion of accumulated supplier capital is destroyed. All firms belong to the representative household, which consumes the final good and supplies labor to firms.

We introduce a working capital constraint in the spirit of Neumeyer and Perri (2005). Specifically, firms must borrow working capital due to a friction in the technology for transferring resources to the households that provide labor services. We then demonstrate that the model can account for the cross-sectional patterns observed in the data. In particular, the model captures the positive impact of supply chain disruption shocks on investment in supplier capital, as firms attempt to restore their capital stock. This effect is quantitatively smaller for more constrained firms, which aligns well with the data. Additionally, we show that both stock returns and revenue are lower for firms that experience supply disruption shocks, with the effect being particularly pronounced for more financially constrained firms.

We use the model to study the impact of an aggregate increase in supply chain disruptions. Specifically, we consider an environment where firms experience a one-period increase in the severity of supply disruptions and then trace the economy's transition back to its steady state. With a shock magnitude similar to that observed by firms in recent years, our model predicts that the economy requires approximately ten quarters to fully recover. Firms' ability to accumulate supplier capital through costly investment serves as an important endogenous margin of adjustment in the aftermath of such crises. Furthermore, we find that limiting this ability by imposing counterfactually high adjustment costs can significantly delay the recovery.

Related Literature. This paper is related to several strands of the literature. This paper constructs an index of supply chain disruptions at the individual firm level, setting it apart from other measures of supply chain disruptions. Using 200 million individual transactions that comprise the universe of U.S. seaborne imports, we are able to construct an index of supply chain disruptions at an unprecedented level of granularity. In contrast, other supply disruptions indices are primarily aggregate. The Bloomberg Supply Constraint Indicator is an aggregate index that represents a single common factor extracted from a set of supply-related indicators, including information on supplier deliveries and business backlogs. Global

Supply Chain Pressure Index (GSCPI) was designed to measure disruptions in global supply chains based on factors such as supplier delivery times, inventory-to-sales ratios, and transportation costs.[2] The KPMG Supply Chain Stability Index measures how well organizations deal with the ups and downs of market volatility; there are nearly 30 key variables and performance indicators underlying the index.[3] The Flexport Ocean Timeliness Indicator shows the average amount of time is takes cargo to be transported from a factory to its destination port.[4] There are two notable exceptions. The first one is the recent study by Bai, Fernández-Villaverde, Li and Zanetti (2024) who construct an index of supply disruptions aggregating granular measures of port congestion around the world. The second one is Blaum, Esposito and Heise (2023) who construct a measure of shipping time risk using transaction-level import data on ocean shipments from the U.S. Census Bureau combined with data on oceanic wave conditions.

This paper contributes to a growing literature studying aggregate effects of supply chain disruptions (e.g., Carvalho et al., 2021; Bonadio et al., 2021; Alessandria et al., 2023; Comin et al., 2023; Acharya et al., 2023; Bai et al., 2024; Heise et al., 2024; Amiti et al., 2024). A recent important topic within this literature is supply chain disruptions caused by climate risk (Blaum et al., 2023; Castro-Vincenzi et al., 2024). An influential related strand of the literature theoretically studies the formation, fragility and failures in supply networks (e.g., Ostrovsky, 2008; Elliott et al., 2014; Ambrus and Elliott, 2021; Elliott et al., 2022; Acemoglu and Tahbaz-Salehi, Forthcoming). Our paper is the first to measure supply disruptions at the individual firm level and study the impact of those disruptions on firm-level outcomes

[2] https://www.newyorkfed.org/p1, Benigno, di Giovanni, Groen and Noble (2022).
[3] https://kpmg.com/p1.
[4] https://www.flexport.com/p1.

both empirically and quantitatively.

On a conceptual level, this paper also relates to the literature that considers different types of capital in the production process of firms. Heise (2016) is an early formalization of the firm-to-firm relationship capital in the context of the shock pass-through. More broadly, literature has also studied organizational capital (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013, 2014), intangible capital (McGrattan, 2020; Bhandari and McGrattan, 2021; Crouzet et al., 2022), customer capital and consumer base (Bils, 1989; Rotemberg and Woodford, 1991; Gourio and Rudanko, 2014; Sedláček and Sterk, 2017; Paciello et al., 2019). Correspondingly, in our quantitative model, supplier capital is a state variable, and firms endogenously decide how much to invest in it. We use the model to show that these investments are an important margin of adjustment in the aftermath of supply disruptions.

A large body of literature has argued that frictions in financial markets can constrain investment decisions, forcing firms to rely on internal funds (Gomes, 2001; Moyen, 2005; Hennessy and Whited, 2007). Related studies show that financially constrained firms also cut back on innovation activities (Duval, Hong and Timmer, 2020) and pollution abatement efforts (Xu and Kim, 2022). In this paper, we provide empirical evidence that financially distressed firms tend to invest less in supplier capital, and experience a larger decline in stock returns and revenue upon receiving a supply disruption shock.

We also contribute to a well-established literature on supply chain management that investigates the relationship between firms' supplier development efforts and their performance (e.g., Krause et al., 2007; Villena et al., 2011). The term "supplier development" was introduced by Leenders (1966) to describe firms' efforts to increase the number of suppliers and improve suppliers' performance. In the quantitative model we develop in this paper, we conceptualize supplier capital as capturing the number and size of suppliers a firm has; firms can accumulate this capital over time through costly investments. In this sense, we view the buildup of supplier capital as one manifestation of supplier development.

Outline. The remainder of the paper is structured as follows. Section 2 describes the data we use and discusses the construction details of the supply disruptions index. We present central empirical results in Section 3. Section 4 develops a firm dynamics model with supplier capital. Section 5 studies the impact of an aggregate supply disruption shock and presents other quantitative results. Section 6 concludes.

2 Data

In this section, we describe the data we use and lay out the methodology for measuring firm-level supply disruptions.

2.1 Overview of the Data

S&P Global Panjiva is a comprehensive bill of lading (BoL) database encompassing more than a billion shipment-level records for cross-border trade transactions. The raw data for U.S. imports consists of approximately 200 million records, ranging from 2007 to the present. The U.S. data only include seaborne import, and account for about one half of the overall U.S. import.[5]

[5] Flaaen, Haberkorn, Lewis, Monken, Pierce, Rhodes and Yi (2021) argue that these data accord well with U.S. Census Bureau aggregate series. In principle, using the BoL data for Mexico one can account for an important proportion of land shipments. Panjiva also offers shipment-level information for 14 countries. In this study, we focus on U.S. imports.

The dataset consists of bills of lading from the U.S. Customs and Border Protection (CBP), which are accessible under the Freedom of Information Act of 1966 (FOIA). A bill of lading is a legal document that serves as evidence that a shipment has been transported from its origin to its final destination. Companies are required to complete various fields in each bill of lading, such as shipper (exporter) and consignee (importer) names and addresses, descriptions of goods, vessel name, transport company name, ports of lading (loading) and unlading (unloading), weight and container details. Panjiva also imputes several supplementary variables, such as shipment volume in twenty-foot equivalent units (TEUs) and value in U.S. dollars, based on container information and other shipment attributes. Table C1 provides the description of key variables available in the data.

2.2 Details on Sample Construction

The starting point of the sample construction is the universe of shipments imported by U.S. consignees. We drop observations with the missing firm identifier, `conpanjivaid`. Carriers and logistics companies are also excluded since they may be recorded as consignees when handling end-to-end shipments. To address this issue, we created a list of the top-100 logistics companies and freight forwarders and excluded observations where these companies are listed as consignees. Additionally, we utilize a cross-reference file to obtain `companyid` (the S&P identifier of firms) for each `conpanjivaid`. However, not all consignees can be matched, as numerous small private companies engage in global import/export activities, and these entities are too small for Capital IQ to cover due to insufficient information. Observations with missing `companyid` are subsequently removed from the sample.

Throughout the analysis, we combine the data to the level of the ultimate parent company. To this end, we use the cross-reference file provided by S&P Global to associate each `companyid` with its ultimate parent company (`ultimateparentcompanyid`). Observations with missing ultimate parent IDs are discarded, though this affects only a small number of observations. In order to ensure we are analyzing actively trading US firms, ultimate parent companies that were active for less than 24 months during the sample period are dropped. In order to alleviate redaction concerns, we exclude U.S. firms with the highest average (per month) shares of missing identifiers for the shipping company; i.e., we keep firms with the average share of monthly records with missing `shppanjivaid` of no more than 10 percent. Furthermore, we focus on the time period starting from 2013m1, as earlier data (going back to 2007m1) have relatively high share of missing US firm identifiers (see Figure C1 in Appendix).

2.3 Construction of the Index

Methodology. Our primary objective is to construct an index of supply chain disruptions at the *firm*-level. Conceptually, we measure supply disruptions as a fraction of established trade pairs which are temporarily inactive (to be discussed below). The main idea is to construct an index of supply disruptions for each HS 2-digit product category utilizing the entire dataset and then average those indices for each ultimate parent firm using fractions of the total firm-level import value accounted for by individual HS 2-digit product codes as weights.

Specifically, an index of supply disruptions for firm i at time t is

$$\text{Index}_{it} = \sum_{j \in \mathcal{N}_{it}} W_{ijt} \times \widehat{\text{Index}}_{jt}, \tag{1}$$

where $\widehat{\text{Index}}_{jt}$ is an index of supply disruptions within product category j at time t, $\mathcal{N}_{it}$ is the set of HS 2-digit product categories firm i imported at time t, and W_{ijt} is the share of the total import value of firm i accounted for by product category j at time t:

$$W_{ijt} = \frac{\text{Tot. value}_{ijt}}{\sum_{j \in \mathcal{N}_{it}} \text{Tot.value}_{ijt}}. \tag{2}$$

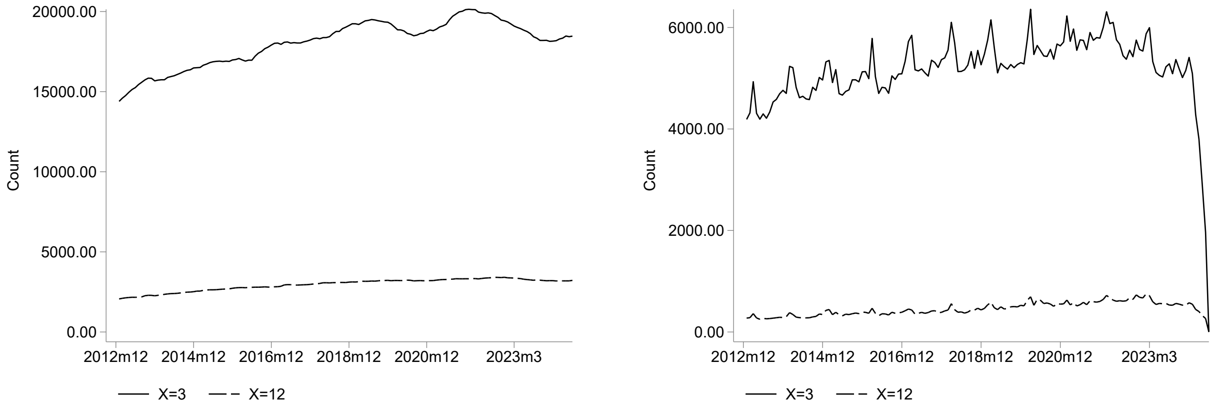
The import value is measured in U.S. dollars (variable `valueofgoodsusd` in Panjiva dataset); we deflate all nominal variables using aggregate price index data. We construct our raw index at a monthly frequency but use annual weights (i.e., W_{ijt} in Equation (2) is constant across months within any given year for firm i and product j) to reduce the impact of short-term demand fluctuations and potential noise.

We next describe how we construct a set of HS 2-digit disruption indices, $\{\widehat{\text{Index}}_{jt}\}$.

Measuring Supply Chain Disruptions. We define our disruptions measure at each time t to capture the fraction of *established* trading partners (defined as the firm-pairs that trade regularly) that *temporarily* cease trading activities:

$$\text{Disruption rate}_{jt}(X, p, v) = \frac{|\{\text{established}(X, p) \cap \text{inactive} \cap \text{active in future}(v)\}_{jt}|}{|\{\text{established}(X, p)\}_{jt}|}. \tag{3}$$

Figure 1: Time-Series Behavior of Index Components



(A) Established and recently active (B) Temp. inactive established

Notes: Figure 1 consists of 2 panels. Panel (A) plots the count of established and recently active trade pairs for HS code 39 (plastic). Panel (B) depicts the count of temporarily inactive trade pairs. In both panels, the solid line corresponds to the case where the pair needs to trade for 3 months over a 12 month period ($X = 3$) to become established, while the dashed line corresponds to the case $X = 12$. A trade pair is considered recently active if it was active in at least one month over the preceding 12 months ($p = 12$), and recovery is determined over the subsequent 6 months ($v = 6$).

A trade pair is established at time t if the pair has actively traded for X months over a consecutive twelve months period in our sample and if the pair has been active at least once between $t - p$ and $t - 1$. The disruption rate is the fraction of established pairs that are inactive at time t but becomes active in the future between $t + 1$ and $t + v$. The restriction on being active again in the future enables us to focus on temporary disruptions (as opposed to permanent dissolution of the trade pair). $X \in \{3, 6, 9, 12\}$, $p \in \{12, 24, 36\}$ and $v \in \{1, 2, 6, 12\}$ are tuning parameters.

We consider three different horizons over which we determine whether the trade pair was active in the recent past: $p \in \{12, 24, 36\}$. This choice is motivated by the observation that almost all inactive trade pairs, conditional on recovering in the future, become active again within 24 months (see Figure C6 in Appendix). Finally, in determining whether trade pairs become active in the future, we consider the following horizons: $v \in \{1, 2, 6, 12\}$.

In order to give a sense of what accounts for the time-series behavior of the disruption rate, Figure 1 plots the time series for the numerator and denominator of Equation (3) ($X = 3$ or 12, $p = 12, v = 6$ for HS code 39 (plastics)). Panel (A) demonstrates that the number of established and recently active trade pairs is smooth; as the requirement for being established becomes more conservative (X rises), the denominator of (3) declines. In turn, Panel (B) shows that the number of temporarily inactive trade pairs is volatile and exhibits seasonality.

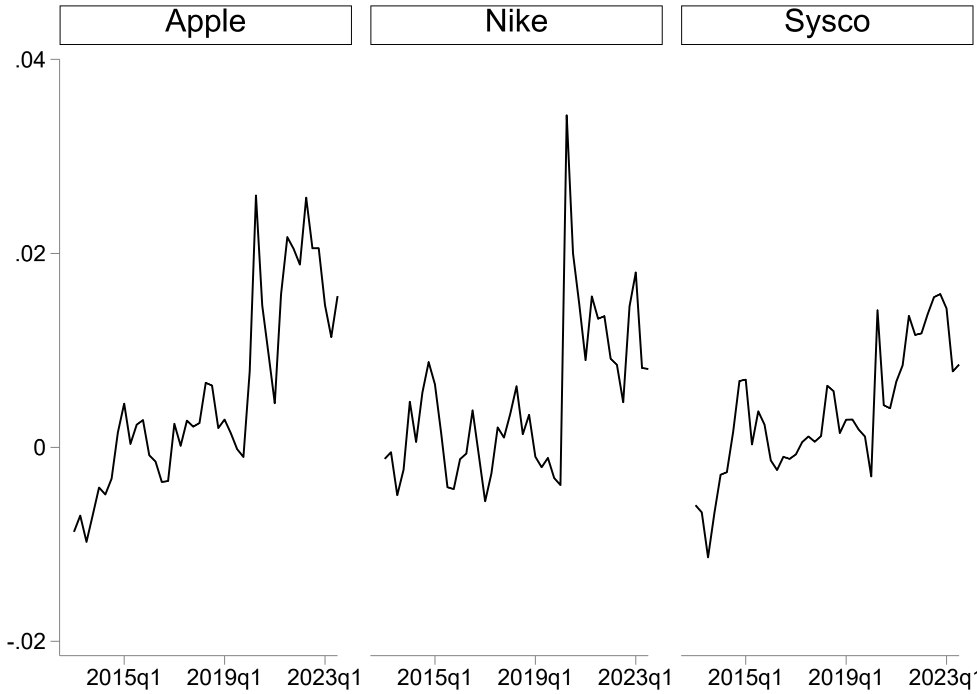
The HS 2-digit product category index $\widehat{\text{Index}}_{jt}$ represents the mean of time series taken across all combinations of parameters X, p and v (48 time series in total); these time series are deseasonalized and smoothed using a 3-month rolling window.[6] The index is then re-scaled such that it is on average zero for the time period prior to 2020m1.

End-of-sample Treatment. Since our definition of the disruption rate includes the notion of temporarily inactive trade pairs, the identification of disrupted trade pairs becomes challenging toward the end of the sample as we do not observe which inactive pairs will become active again. This issue is illustrated by the right panel of Figure 1, where the number of temporarily inactive trade pairs falls to zero as it gets closer to the end of the sample time period.

One can in principle impute the number of inactive trade pairs which eventually recover by exploiting the very stable relative recovery rates of trade pairs over various horizons (see Figure C3 in Appendix for an illustration and Liu et al. 2023 for details). In this paper, we

[6] Another approach to summarizing the information in the underlying time series involves extracting the first component through principal component analysis (PCA). Upon experimenting with PCA, we found that the results are generally comparable. We chose to use the mean across the time series as the baseline index for the sake of easier interpretation.

Figure 2: Firm-Level Disruptions: Select Firms



Notes: Figure 2 plots supply disruption index for select firms. See Section 2.3 for details of the index construction.

chose not to use an imputation scheme, and essentially do not utilize the last 12 months of the data.

Discussion. Even though it is feasible to construct an index of supply disruptions directly on a firm-by-firm basis, we chose not to pursue this approach in this paper for two reasons. First, we found that indices constructed directly at the firm level are noisy for a number of public firms that have few trading partners. However, we confirmed that the index computed directly on a firm-by-firm basis is strongly positively correlated with the index constructed using firms' exposure to various product categories for a subset of firms with sufficiently large number of suppliers.

Second, and perhaps more importantly, our firm-level index of supply chain disruptions reflects, by construction, a firm's exposure to supply disruptions across product categories. In other words, our index of disruptions is less likely to be driven by the idiosyncratic demand of a given firm, as it incorporates information from a broad set of firms. Nevertheless, to alleviate the impact of demand effects, we also provide results from a number of IV regressions in the section with empirical results (see Section 3 for details) and show that these regressions deliver qualitatively similar but quantitatively stronger results as compared to OLS regressions.

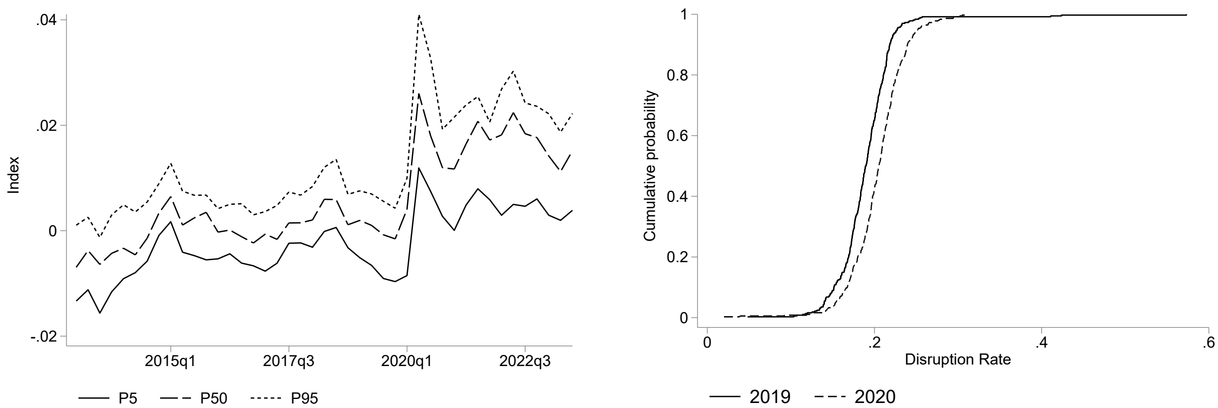
2.4 Firm-level Supply Disruptions

Turning to firm-level analysis, we averaged the index at the quarter level to match the time frequency of Compustat data. Figure 2 plots the index of supply disruptions for several select public firms in the sample: Apple, Nike, and Sysco. The numbers on the vertical axis show the change in the share of temporarily inactive established trade pairs relative to the historical (pre-2020) average.

The data show that firms experienced supply disruptions of varying magnitudes and durations. Specifically, Apple faced a spike in disruptions of about 2.5 percentage points (pp) above the historical average at the beginning of 2020, while Nike saw an increase of more than 3pp. However, while disruptions for Nike subsided fairly rapidly, Apple experienced a decline in supply chain disruptions toward the end of 2020, followed by a second wave of supply chain pressures in 2021-2022. Meanwhile, Sysco experienced a relatively modest increase in disruptions.

Panel (A) of Figure 3 shows the time-series evolution of percentiles in the firm-level

Figure 3: Firm-Level Disruptions: Time-Series and Cross-Section



(A) Firm-Level Disruptions: Percentiles

(B) CDF of Disruption Rates

Notes: Figure 3 contains two panels. Panel (A) plots various percentiles (by quarter) of the firm-level supply disruptions index. See Section 2.3 for details of the index construction. Panel (B) plots the cumulative density function of disruption rates for years 2019 (solid line) and 2020 (dashed line).

index distribution over the sample period. Several observations stand out. First, the cross-sectional distribution of disruptions was relatively concentrated prior to 2020, with the P5-P95 range of about 1pp. Following an overall increase in disruptions in 2020 (illustrated in Panel (B)), the distribution spread considerably, with the P5-P95 range reaching 3pp. In subsequent years, the average level of disruptions decreased, though overall dispersion persisted, reflecting the ongoing pressures that some firms continue to face in their supply chains. Notably, the bottom five percent of firms in terms of supply chain pressures saw a near-complete normalization of conditions in 2021.

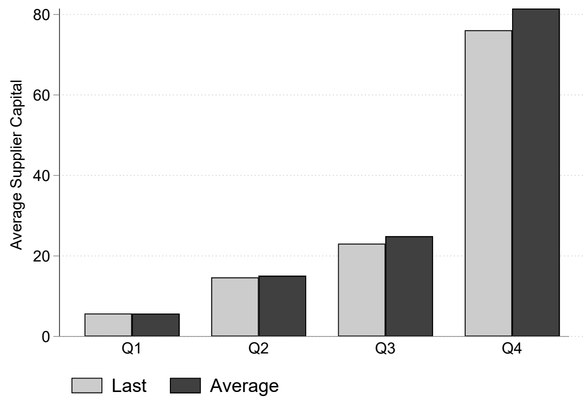
2.5 Measuring Supplier Capital

Provided that we measure supply chain disruptions as a fraction of established trade pairs that are temporarily inactive, we chose to measure a firm's international supplier capital as the total import value in U.S. dollars accounted for by established trade partners with whom the firm recently traded. This metric, therefore, captures both the number of established trade partners and their importance in terms of trade value. We chose tuning parameters $X = 3$ and $p = 24$; i.e., trade occurred with that partner in at least 3 months over a 12-month period, and we recorded activity of that pair over the preceding 24 months. We chose this set of tuning parameters to maximize our sample, since there is a number of firms that do not have many suppliers for larger values of X and which would have otherwise been dropped from our final sample.

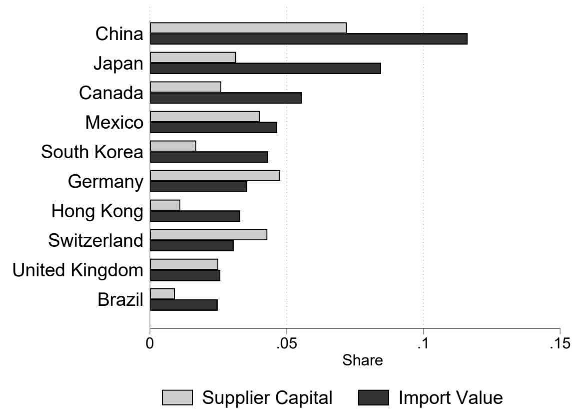
Importantly, if a given established partner is not active at time t, we record the import value of the last transaction with that supplier (which, by construction, occurred within the preceding 24 months) to compute the supplier capital at a given time period. We also considered an alternative approach, where supplier capital at time t is the average transaction value over the last $p = 24$ months; as we show below, this alternative does not materially impact our measure of supplier capital.

Figure 4 demonstrates how supplier capital is related to both the number of established trade partners and the total import value. Panel (A) plots the average supplier capital by quantile of the number of established trade partners. The distribution of the number of established trade partners is highly right-skewed, with the $25^{th}, 50^{th}$, and 75^{th} percentiles being 6, 15, and 37, respectively. The panel demonstrates that firms with a larger number of established trade partners import more value from them. Even though these two metrics are highly correlated, we chose to measure supplier capital using monetary value, since it captures not only the number but also the relative importance of established trade partners. Lastly, the figure shows that the difference in how supplier capital is measured—whether using the value from the last transaction or the average value over the last 24 months—is

Figure 4: Supplier Capital: Relationship with the Number of Established Trade Pairs and Total Trade Value



(a) Supplier capital by quantile of the number of established trade partners



(b) Supplier capital and import value shares for largest exporters to the U.S.

Notes: Figure 4 consists of 2 panels. Panel (A) plots the average supplier capital by quantile of the number of established trade partners. If a given established partner is not active at time t, we record the import value of the last transaction with that supplier ("last"). We also consider an alternative with supplier capital at time t being the average transaction value over the last $p = 24$ months ("average"). Panel (B) plots supplier capital and import value shares accounted for by the largest 10 exporters to the U.S.

minimal. We chose to use the value from the last transaction throughout the paper.

Panel (B) plots supplier capital and import value shares accounted for by the largest exporters to the U.S. The figure reveals several patterns. First, even though supplier capital is measured in terms of trade value, the distribution of supplier capital across countries is quite different from that of import value. This reflects that the notion of supplier capital is conceptually distinct from total trade volume. Furthermore, the data reveal that the largest exporting countries to the U.S. (China and Japan) account for a disproportionately small fraction of supplier capital. In contrast, European countries such as Germany and Switzerland account for a disproportionately high share of supplier capital.

2.6 Summary Statistics

Table 1 provides summary statistics for select quarters.[7] The size distribution of firms in our sample is right-skewed, with the 90^{th} percentile of any common size metric (physical capital, employment, assets and sales) being much further from the median as compared with the difference between the median and the 10^{th} percentile. As per firm-level supply chain disruptions, we see a dramatic increase in the average index between 2020Q1 and 2021Q1 (from 0.3pp to 1.1pp). At the same time, the cross-sectional dispersion in the index has also risen over that time period, mirroring the patterns depicted in Figure 3.

The data reveal that the firm-size distribution of supplier capital is highly right-skewed: a typical firm imports approximately 3.5 million USD worth of products from established trade partners, while firms in the 10^{th} and 90^{th} percentiles import 0.18 and 54 million USD, respectively. The coefficient of Kelley skewness for supplier capital is 0.87, which is lower than for physical capital (0.96) and employment (0.92).

3 Empirical Results

We first document and report several empirical facts about supplier capital and supply chain disruptions in Section 3.1; we structure these observations around the three key facts. Subsequently, we discuss critical supply chains in Section 3.2.

[7]Since many public firms have few trading partners (see Figure C4 in Appendix), in our subsequent analysis we chose to focus on the set of Compustat firms with at least 50 unique suppliers.

Table 1: Summary Statistics: Select Quarters

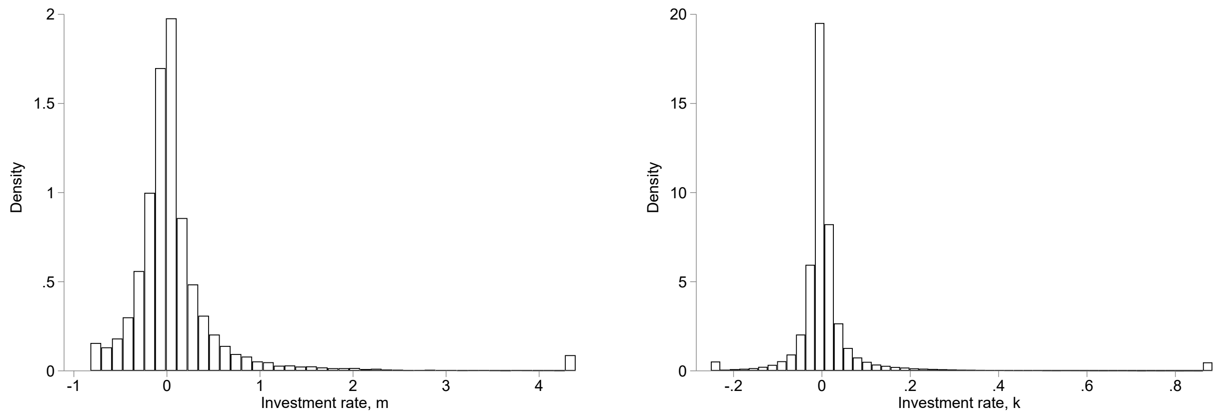
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
2019Q1						
Capital (Log)	3738	5.094	3.559	0.235	5.494	9.323
Sup. Capital (Log)	846	1.265	2.295	-1.689	1.305	3.929
Employment (Log)	3319	0.174	2.867	-3.990	0.531	3.707
Sales (Log)	3350	4.662	2.996	0.557	5.217	8.019
Assets (Log)	3598	6.280	3.155	2.220	6.769	9.957
Leverage	3232	0.295	0.221	0.014	0.281	0.601
Index	1597	0.002	0.005	-0.003	0.002	0.006
Sup. Concentration	1079	0.689	0.289	0.271	0.716	1.000
Rel. Strength	1218	0.584	0.261	0.294	0.500	1.000
2020Q1						
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Capital (Log)	3645	5.154	3.531	0.362	5.579	9.349
Sup. Capital (Log)	849	1.237	2.312	-1.648	1.302	4.097
Employment (Log)	3170	0.206	2.859	-3.875	0.569	3.736
Sales (Log)	3273	4.576	3.005	0.463	5.118	7.942
Assets (Log)	3497	6.326	3.092	2.270	6.792	9.937
Leverage	3080	0.306	0.221	0.021	0.297	0.609
Index	1575	0.003	0.006	-0.006	0.004	0.009
Sup. Concentration	1080	0.698	0.281	0.289	0.746	1.000
Rel. Strength	1230	0.579	0.262	0.288	0.500	1.000
2021Q1						
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Capital (Log)	3683	5.033	3.536	0.357	5.359	9.317
Sup. Capital (Log)	851	1.180	2.362	-1.720	1.254	4.047
Employment (Log)	3215	0.159	2.830	-3.805	0.475	3.710
Sales (Log)	3248	4.608	3.029	0.465	5.133	8.063
Assets (Log)	3492	6.381	3.035	2.480	6.756	9.991
Leverage	3082	0.280	0.218	0.013	0.262	0.576
Index	1611	0.011	0.007	0.004	0.012	0.018
Sup. Concentration	1090	0.707	0.278	0.295	0.755	1.000
Rel. Strength	1224	0.568	0.263	0.287	0.491	1.000

Notes: Table 1 provides summary statistics for select quarters. *Capital* is a measure of physical capital; *Sup. Capital* is the total import value accounted for by established trade partners which were recently active ($X = 3; p = 24$); *Employment* is the number of employees, linearly interpolated in adjacent years; *Sales* is quarterly sales, *Assets* is the total amount of assets; *Leverage* is the firm's debt-to-assets ratio; *Index* is an index of firm-level supply disruptions; *Sup. Concentration* is a measure of supplier concentration; *Rel. Strength* is a measure of relationship strength.

3.1 Stylized Facts about Supplier Capital and Supply Chain Disruptions

Fact 1: Distribution of supplier capital growth rates is highly dispersed. We look into distribution of supplier capital growth rates. Panel (A) of Figure 5 shows that the mean of distribution is 0.107, and the distribution is very dispersed (interdecile range is 0.80

Figure 5: Distributions of Capital Growth Rates



(A) Supplier capital

(B) Physical capital

Notes: Figure 5 consists of 2 panels. Panel (A) plots distribution of supplier capital growth rates $\frac{m_{it+1}-m_{it}}{m_{it}}$; Panel (B) plots distribution of physical capital growth rates. The data are winsorized at 1 and 99 percentiles.

and standard deviation is 0.65). For comparison, Panel (B) plots the distribution of physical capital growth rates which exhibits a much smaller dispersion (interdecile range is 0.10 and standard deviation is 0.12). Physical capital also exhibits a high degree of lumpiness (Cooper and Haltiwanger, 2006; Bai, Li, Xue and Zhang, 2022), as about 40 percent of growth rates are less than one percent in absolute value (the corresponding number for supplier capital is 8.6 percent).

Fact 2: Supply chain disruptions are associated with positive investment in supplier capital, although the effect is smaller for more leveraged firms. We then examine the effect of supply chain disruptions on the firm investment in supply chain capital. We measure investment into supplier capital as $\Delta \log m_{i,t+k}$, where $m_{i,t}$ denotes supplier capital of firm i at time t. Similarly, investment into physical capital is defined as $\Delta \log k_{i,t+1}$, where $k_{i,t}$ is the book value of the tangible capital stock of firm i at time t.

Our key independent variable is $\text{Index}_{i,t}$ which is the firm-level index of supply disruptions constructed in Section 2.3, which captures the total supply chain disruption experienced by a company. We use firm's leverage to proxy for financial conditions; financial leverage $l_{i,t}$ is the ratio of firm's debt (both short- and long-term) to total assets (the precise definition of this and other variables is provided in Appendix A.4).

We estimate different versions of the following model:

$$\Delta \log y_{it+k} = \beta_0 \text{Index}_{it} + \beta_1 \text{Index}_{it} \times l_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{4}$$

where $\mathbf{X}_{it-1}$ is a vector of controls that includes the intercept, year-quarter and firm fixed effects, as well as lagged leverage, lagged logarithms of the firm's physical and supplier capital stocks.

Management literature on supply chains has proposed several firm-level metrics of supply chain management, which have been found to play an important role in explaining recovery speed from sourcing interruptions (Jain, Girotra and Netessine, 2021), inventory performance (Jain, Girotra and Netessine, 2013), and predicting stock returns (Jain and Wu, 2023). We construct and control for two commonly used metrics—supplier concentration and a measure of relationship strength—to establish robustness of our results to these measures of firms' supply chain management strategies. Details on how we construct these measures are provided in Appendix A.1.

The dependent variable y is either physical k or supplier capital m. Our coefficients of interest are β_0 and particularly β_1, which capture the main and interaction effects of supply chain disruptions on firm-level investment. Standard errors are clustered at the firm level. We winsorize variables at top and bottom one percent to reduce the impact of outliers.

Table 2: Supply Chain Disruptions and Firm Investment in Supplier Capital

	$\Delta_t^{t+1} \log m$		$\Delta_t^{t+2} \log m$	
	(1)	(2)	(3)	(4)
Index	0.0052	0.0165**	0.0060	0.0294**
	(0.005)	(0.007)	(0.009)	(0.013)
Index x l		-0.0444***		-0.0848***
		(0.016)		(0.030)
l		-0.0511**		-0.1242***
		(0.025)		(0.048)
Year-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R^2	0.072	0.074	0.116	0.119
N	33250	32034	32469	31297

Notes: Table 2 reports OLS estimates of Equation (4). The dependent variable is investment rate into supplier capital $\Delta_t^{t+k} \log m_{it+1}$ where $k \in \{1, 2\}$. *Index* is a firm-level index of supply chain disruptions constructed in Section 2.3; l is a lagged value of firm's leverage. The vector of controls includes year-quarter and firm fixed effects, a standardized, lagged measure of supplier concentration, a standardized, lagged measure of relationship strength, as well as a standardized, lagged inventory-to-sales ratio. Standard errors are clustered at the firm level. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

Table 2 presents OLS estimates for investment into supplier capital. According to column 1, the effect of disruptions on investment in supplier capital accumulation is positive, although not statistically significant. The point estimate suggests that a one standard deviation increase in the index is associated with about a 0.5pp increase in the investment rate $\Delta \log m_{it+1}$. Column 2 reveals substantial heterogeneity in responsiveness to supply disruption shocks across firms. The interaction term with firm leverage is negative and statistically significant at the 1 percent level. The estimates indicate that a one standard deviation increase in the supply disruptions index for firms with a 10pp higher leverage is associated with 0.4pp lower investment rate. This result highlights that the positive average effect reported in column 1 masks a significantly weaker response from leveraged firms.

In columns (3)-(4), we study the impact of supply disruption shocks on firms' investment over a two-quarter horizon. Overall, the estimates increase in magnitude at this longer horizon, and statistical significance also rises. We interpret this as a reflection of the dynamic nature of investment decisions and the persistent role of financial conditions in shaping future investment choices.

Controlling for Demand. By construction, our firm-level index of supply chain disruptions measures the exposure of a firm to supply disruptions across product categories. In other words, the underlying raw index of disruptions at the product level is unlikely to be driven by the idiosyncratic demand of any given firm, since it incorporates information across a broad set of firms. Nevertheless, in order to further alleviate the impact of demand effects, we also provide estimates for a number of IV regressions. Conceptually, our instrument is based on the number of U.S. firms with which the established foreign shippers of a given U.S firm trade in a given time period, excluding the focal U.S. firm (see Appendix A.3 for details). We conduct these calculations at the firm level within each product category and subsequently aggregate them to the firm-quarter level using firm import values at the product level as weights. Intuitively, this instrument is designed to capture the notion that when a given U.S. firm is inactive, and this inactivity coincides with a drop in activity among that U.S. firm's established shippers, it is likely that the inactivity is driven by supply considerations rather than a decline in the given firm's demand.

Qualitatively, we find that IV estimates are similar to those reported in Table 2, but they become larger in absolute value. For example, the interaction term in column (4) of Table A1 suggests that a one standard deviation increase in the supply disruptions index for firms with 10 percentage points higher leverage is associated with a 1.9 percentage point lower investment rate—an effect nearly four times larger than the OLS estimates reported

Table 3: Supply Chain Disruptions and Firms' Revenue and Returns

	Revenue				Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔIndex	-0.30***	-0.15***	-0.15***	-0.25***	-0.27***	-0.26***	-0.26***	-0.27***
	(0.07)	(0.04)	(0.04)	(0.05)	(0.09)	(0.09)	(0.09)	(0.10)
RS_{t-1}			0.84**	-0.12			-0.03	-0.07
			(0.33)	(0.35)			(0.13)	(0.14)
SC_{t-1}			-0.06	0.08			-0.12	-0.07
			(0.13)	(0.14)			(0.10)	(0.11)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Controls	No	No	No	Yes	No	No	No	Yes
R^2	0.01	0.84	0.84	0.90	0.17	0.21	0.21	0.23
N	86,456	86,382	86,382	50,650	307,053	307,048	307,048	227,648

Notes: Table 3 reports OLS estimates of the following equation:

$$y_{it} = \beta\Delta\text{Index}_{it} + \lambda\mathbf{X}_{it-1} + \varepsilon_{it},$$

where the left-hand side variable is either firm revenue or stock returns. *Revenue* is constructed as firm revenue divided by total assets. *Returns* is the logarithm of the stock returns. *rev* and *ret* are multiplied by 100 to facilitate interpretation. ΔIndex represents the changes in the (standardized) disruption index. RS is the lagged measure of relationship strength, and SC is the lagged measure of supplier concentration. Controls include the lagged logarithm of firm size, lagged market-to-book ratio, lagged net price margin, and lagged accrual. Standard errors are clustered at the firm level. All variables are winsorized at the top and bottom 1 percent. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

earlier.

In Appendix A.3, we also investigate the impact of supply chain disruptions on investment in physical capital. We find a negative and statistically significant effect at the aggregate level, which becomes even more pronounced for leveraged firms. However, both the direct effect and the interaction term are quantitatively smaller as compared to the case of supplier capital investment.

Fact 3: Supply chain disruptions are associated with lower stock returns and revenue; the effect is more negative for financially distressed firms. In the next set of results, we evaluate the impact of supply chain disruptions on financial returns and firm revenue (see Table 3). Columns (1)–(4) report results for revenue, while columns (5)–

(8) show results for stock returns. We aim to examine how current period supply chain disruptions affect firm revenue and stock returns, and therefore, we use changes in our supply chain disruption index, or ΔIndex, as the main independent variable. For each dependent variable, we gradually include additional controls. The point estimates of ΔIndex are consistently negative and significant at the 1 percent level, suggesting that supply chain disruptions are associated with lower revenue and stock returns. The estimates are also economically significant. In our preferred specifications with full controls (columns (4) and (8)), the results indicate that a one standard deviation increase in index is associated with a 1.4 and a 1.9 percent decrease in the standard deviation of revenue and stock return, respectively.[8]

We next show that the returns and revenue of financially constrained firms decline by more when supply disruptions increase. Table 4 reports our results. We use three common measures in the literature to gauge whether firms are financially constrained: the long-term debt ratio (LT), the Whited and Wu (2006) measure (WW), and the Kaplan and Zingales (1997) measure (KZ). For each period, we divide each of the three measures into five quintile brackets, using bracket numbers as corresponding variables. Firms with the lowest values are placed in bracket 1, while those with the highest values are placed in bracket 5. Consequently, higher values of LT, WW, and KZ indicate that the firms are more financially constrained.

Overall, we find that the interaction terms between ΔIndex and each measure of financial constraints considered are always negative and almost always significant at least at the 5 percent level. These results suggest that the revenue and stock returns of more financially constrained firms decline more strongly when supply chain disruptions increase.

[8] Sample standard deviations of revenue and stock returns are 18.1 and 13.6, respectively.

Table 4: Supply Chain Disruptions and Firms' Revenue and Returns: Role of Financial Constraints

	Revenue			Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIndex x LT_{t-1}	-0.08***			-0.10**		
	(0.03)			(0.05)		
ΔIndex x WW_{t-1}		-0.18**			-0.19**	
		(0.07)			(0.09)	
ΔIndex x KZ_{t-1}			-0.09***			-0.07
			(0.03)			(0.05)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.90	0.90	0.90	0.12	0.12	0.12
N	50,349	50,650	50,650	225,966	227,422	227,422

Notes: Table 4 reports OLS estimates of the following equation:

$$y_{it} = \beta_0 \Delta\text{Index}_{it} + \beta_1 \Delta\text{Index}_{it} \times l_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}.$$

Dependent variable *Revenue* is firm revenue divided by total assets; *Returns* is the logarithm of stock returns. Both *rev* and *ret* are multiplied by 100 to facilitate interpretation. ΔIndex represents changes in the standardized supply disruption index, and l_{it-1} is a measure of financial constraints. LT, WW, and KZ are the bracket numbers of assigned quantile brackets based on the long-term debt ratio, the Whited and Wu (2006) measure, and the Kaplan and Zingales (1997) measure, respectively. Controls include the lagged logarithm of relationship strength, supplier concentration, firm size, lagged market-to-book ratio, lagged net price margin, lagged accrual, as well as cross-terms between each of these variables and ΔIndex. Standard errors are clustered at the firm level. All variables are winsorized at the top and bottom one percent. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Additional Results. Appendix A.3 presents a set of additional results. Specifically, we show that while the investment rate in physical capital declines with firm size (as measured by total assets), investment in supplier capital does not appear to vary across size quantiles. We also demonstrate that there is substantial heterogeneity in average supplier capital across NAICS 2-digit industries: mining, utilities, and manufacturing have the highest average supplier capital, while the retail and information sectors have the lowest. At the same time, industries exhibit similar exposure to supply chain disruptions, as the average index is comparable across them.

3.2 Critical Supply Chains

As mentioned in the introduction, securing supply chains, and especially critical supply chains, has become a key concern for policymakers in the U.S. and worldwide. For instance, the White House issued Executive Order 14017, "Executive Order on America's Supply Chains," which outlines U.S. policy objectives for strengthening the resilience of U.S. supply chains, with a particular focus on those critical to the U.S. economy.[9] In this section, we demonstrate that U.S. firms relying heavily on imports of critical products are more exposed to pressures in supply chains.

When analyzing critical supply chains, it is important to work with more disaggregated product categories, as many subcomponents within an HS 2-digit category may not be identified as critical. For example, in a draft list of products deemed critical to the U.S. economy, prepared by the International Trade Administration, electromagnets (including neodymium magnets) (HS 8505) and electric storage batteries (HS 8507) are identified as critical, while primary cells and batteries (HS 8506) and vacuum cleaners (HS 8508) are not.[10] We chose to classify HS 4-digit product categories into critical and non-critical groups. This choice strikes a balance between the granularity of resulting product categories and data availability: while Panjiva data allows analysis up to the HS 6-digit level, in many cases we lack sufficient information to determine how critical a product is at a finer level of disaggregation.

Our measure of how critical a product category is to the U.S. economy is based on the concentration of suppliers within that category. Specifically, the underlying assumption is that if U.S. firms source a given HS 4-digit product category from a small (and concentrated)

[9] https://www.whitehouse.gov/p1. In particular, the Order emphasizes four critical sectors: Public Health, Critical Minerals and Materials, Energy, and Information and Communications Technology.

[10] https://www.trade.gov/p1.

Table 5: HS 4-digit Products by Average HHI

High HHI			Low HHI		
HS Code	**Description**	**Mean HHI**	**HS Code**	**Description**	**Mean HHI**
7611	Aluminum tanks	0.987	8443	Printing machinery	0.050
7203	Iron ores	0.986	6203	Men's clothing	0.049
8905	Light vessels	0.986	4001	Natural rubber	0.048
5805	Woven tapestries	0.984	6307	Used textiles	0.046
5212	Cotton fabrics	0.983	4202	Travel goods	0.034
2515	Marble	0.979	9506	Sporting goods	0.041
5303	Flax, raw	0.975	8504	Electrical transformers	0.041
0504	Whale fins	0.975	9403	Wooden furniture	0.043
0603	Cut flowers	0.975	8708	Vehicle parts	0.023
8602	Railway locomotives	0.975	6403	Leather footwear	0.028

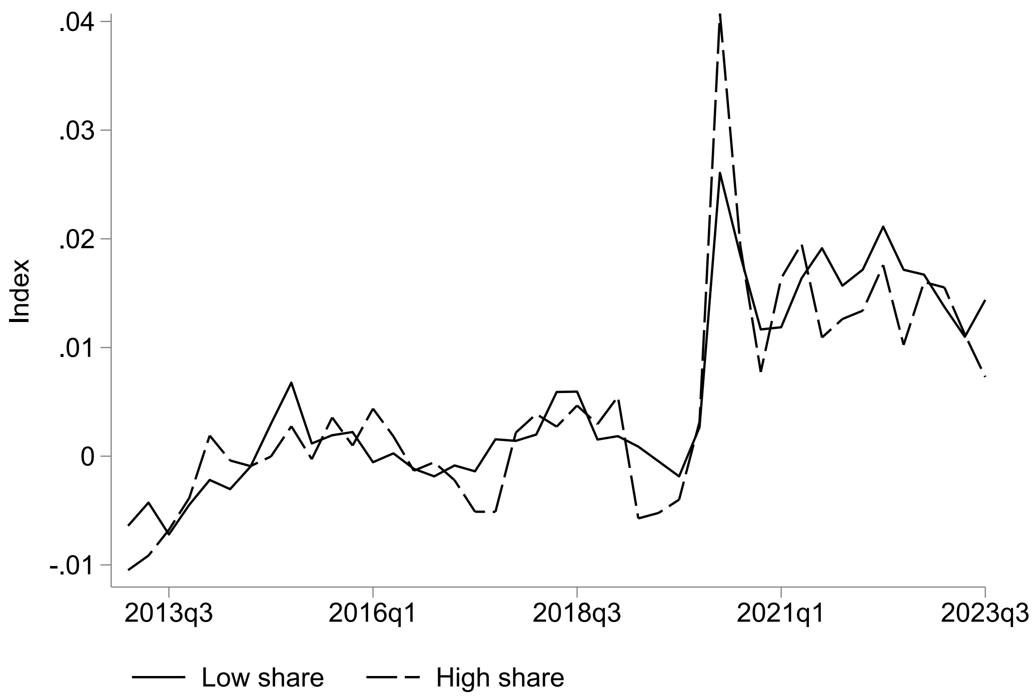
Notes: Table 5 reports a set of HS 4-digit product categories along with the average (over time) concentration of suppliers. Concentration is measured using Herfindahl-Hirschman Index. Higher values mean higher concentration.

number of suppliers, then any disruption affecting one of these suppliers leaves the importing firms with less flexibility to switch to another source. Conversely, a rich and diversified set of suppliers is associated with greater ease in switching to an alternative supplier if necessary.

Table 5 reports a set of HS 4-digit product categories along with the average (over time) concentration of suppliers. The left part of the table lists products with the highest measured concentration, while the right part includes product categories with the lowest concentration statistics. Subsequently, we classify each firm-quarter into two groups based on the share of the total import value of a given firm accounted for by product categories with the highest HHI. In our quantitative implementation, we define product categories as critical if the HHI exceeds 0.9, which roughly corresponds to the 90^{th} percentile of the concentration measure across all product categories. We classify a firm-quarter into the high-share critical products group if at least 75 percent of the firm's total import value in a given quarter is accounted for by critical products. Results are qualitatively similar if this threshold is increased or decreased.

Figure 6 reports indices of supply chain disruptions for groups with high and low shares

Figure 6: Supply Chain Disruptions by Firms with High and Low Share of Critical Imports



Notes: Figure 6 plots the supply disruption index for groups of public firms with high and low shares of critical product imports. HS 4-digit product codes are categorized as critical if the average (over time) supplier concentration exceeds 0.9. Firm i is classified into the "high share" category at time t if the total value of its imports of critical products exceeds 75 percent of its total imports during that time period. See Section 3.2 for details.

of critical imports. An important observation stands out. While the groups exhibit very similar exposure to supply chain disruptions over the last decade, the "high share" group experienced a spike in supply chain pressures in mid-2020 that was nearly twice the size of what the "low share" group experienced. We interpret these results as evidence supporting the efforts of policymakers to improve the resilience of supply chains, particularly with a focus on critical supply chains. The data indicates that firms with high dependence on critical products see a much larger increase in supply chain disruptions during adverse aggregate economic conditions.

4 Model

In this section, we develop a model based on the empirical findings reported in Section 3. Specifically, the model explains the positive investment response in supplier capital and the negative response in physical capital following a supply disruption shock. Importantly, we use the model to demonstrate that firms' ability to accumulate supplier capital through costly investment is a crucial margin of adjustment. By introducing a financial constraint into the economic environment, we can account for the heterogeneous investment response across firms with different leverage.

4.1 Environment

We build a model of industry dynamics with heterogeneous firms. Time in the model is discrete and the horizon is infinite. The economy is populated by heterogeneous firms and a representative household. Firms produce a homogeneous final good. Households own shares in firms, supply labor, and consume the final good.

Technology Every firm i has access to a Cobb-Douglas production technology with returns to scale κ:

$$y(k, m, z, n) = e^{z}\left(k^{\theta} m^{\phi} n^{1-\theta-\phi}\right)^{\kappa}$$

with $\theta, \phi \in (0, 1)$. Every firm produces a homogeneous output y by combining labor n, physical capital k, supplier capital m with corresponding shares $1-\gamma$, θ and ϕ, respectively. The production function is scaled by an idiosyncratic productivity component z.

Idiosyncratic component z follows an AR(1) process with the persistence parameter $\rho_z \in$

$(0, 1)$:

$$z_{t+1} = \rho_z z_t + \varepsilon_{t+1}^z, \quad \varepsilon_{t+1}^z \sim \mathcal{N}(0, \sigma_z) \tag{5}$$

Labor Labor market is frictionless with the wage rate W.

Financing There is a representative household that owns all firms. The proceeds from production, net of investment and adjustment costs, are paid out to the household as dividends. We introduce a working capital constraint in the spirit of Neumeyer and Perri (2005). Specifically, firms need to borrow working capital due to a friction in the technology for transferring resources to the household that provides labor services. To transfer $W_t n_t$ to the household, firms must set aside a fraction η of the wage bill at the beginning of period t^- and the remaining fraction $(1 - \eta)$ at the end of period t^+. Since production becomes available only at the end of the period, firms are required to borrow $\eta W_t n_t$ between t^- and t^+ at an interest rate of R_{t-1}.

Households The economy is populated by a unit mass of identical households. Each household consumes, supplies labor, and saves into firms' shares.

4.2 Firm Optimization

The aggregate state at time t consists of the distribution of firms over the idiosyncratic states $\mu = \mu(k, m, z)$, as well as the value of the aggregate supply disruption shock ζ_t. We index value functions by time index t to reflect their dependence on the aggregate state.

The firm enters the period with pre-determined levels of physical and supplier capitals k and m. Idiosyncratic productivity z is realized at the beginning of the period. Let $v_t(k, m, z)$

denote the value of the firm at the start of the period t given the idiosyncratic state (k, m, z):

$$v_t(k, m, z) = p^{shock} v_t^{cont}(k, \zeta_t m, z) + (1 - p^{shock}) v_t^{cont}(k, m, z). \tag{6}$$

According to Equation (6), with i.i.d. probability p^{shock} firms receive a supply disruption shock at the start of period t, in which case a fraction $1 - \zeta_t$ of the supplier capital they brought into the period gets destroyed. The remaining mass of firms $1 - p^{shock}$ does not experience any disruption shocks. The aggregate shock ζ_t governs the severity of a supply disruption event.

Value function v_t^{cont} in Equation (6) describes the intertemporal choices of the firm:

$$v_t^{cont}(k, m, z) = \pi_t(k, m, z) + \max_{k', m' \geq 0} \left\{ -i_k(k', k) - i_m(m', m) + \mathbb{E}_t \left[M_{t+1} v_{t+1}(k', m', z') \right] \right\}, \tag{7}$$

where firm's operating profits π are defined as:

$$\pi_t(k, m, z) = \max_{n \geq 0} e^z \left(k^\theta m^\phi n^{1-\theta-\phi} \right)^\kappa - W_t n - \underbrace{[R_{t-1} - 1] \eta W_t n}_{\text{net interest on borrowing}} \tag{8}$$

and M_{t+1} is the stochastic discount factor.

In Equation (7), $i_x, x \in \{k, m\}$ denote investments into two types of capital:

$$i_x = x' - (1 - \delta_x)x + AC(x', x), \tag{9}$$

where $AC(\cdot)$ denote capital adjustment costs. We assume that supplier capital does not depreciate. Alternatively, the supply disruptions shocks can be viewed as stochastic depreciation of supplier capital.

Finally, firm's dividends are defined as:

$$Div_t(k, m, z) := \pi_t(k, m, z) - i_k(k', k) - i_m(m', m). \tag{10}$$

4.3 Household Optimization

The representative household maximizes the discounted stream of utilities subject to the budget constraint. We assume that labor is supplied inelastically, and it is normalized to be 1. The wealth is held in one-period firm shares, $\xi_t(k, m, z)$. The price of current shares is ω_0, and the purchase price of new shares is ω_1. The household's dynamic programming problem is:

$$H_t = \max_{c,\xi'} \left[U(c) + \beta \mathbb{E}_t H_{t+1}\right] \tag{11}$$

subject to

$$c + b' + \int \omega_{1,t}(k', m', z') \mathrm{d}\xi_{t+1} \leq W_t + R_t b + \int \omega_{0,t}(k, m, z) \mathrm{d}\xi_t. \tag{12}$$

The right-hand side of (12) represents the resources available to the household; it consists of firm shares from the previous period, as well as labor income and return on bonds. Part of these resources is consumed, and the rest is reinvested into firm shares and a risk-free bond.

Utility We assume log-preferences of the household over consumption $U(c_t) = \log(c_t)$. Let C_t and B_t be the household's consumption and bond policy functions, respectively. Also, let $\Xi_{t+1}(k', m', z')$ be a number of shares purchased in firms which start next period with capital stocks k', m', and idiosyncratic productivity component z'. The detailed definition of equilibrium is relegated to Appendix B.1.

4.4 Parameterization and Model Fit

We set the model period to be one quarter; this aligns with the frequency of our data. We therefore set the discount factor $\beta = 0.99$. We set the returns to scale parameter κ is set to 0.85, which is a standard value used in firm dynamics literature (Khan and Thomas, 2008; Winberry, 2021). The persistence ρ_z of idiosyncratic productivity process is taken from Ottonello and Winberry (2020). We set the idiosyncratic volatility $\sigma_z = 0.10$.

We set the depreciation rate δ to match average quarterly investment rate in the data (0.01). Quadratic adjustment costs are set to match the dispersion of investment rates in the cross-section of firms; we have shown earlier in Figure 5 that supplier capital investment rates are much more dispersed as compared with physical capital investment rates (0.65 and 0.12, respectively). We assume that the entire wage bill needs to be paid in advance and, thus, set $\eta = 1$.

Parameters p^{shock} and $\bar{\zeta}$ govern the occurrence of supply chain disruptions at the steady-state of the model. We use the average disruption rate in the data (0.22) and variance of disruptions (0.01) to simultaneously set $p^{shock} = 0.83$ and $\bar{\zeta} = 0.74$.[11] Figure C5 in Appendix reports the distribution of disruption rates in the data.

Production Technology We obtain production elasticities by estimating the following specification:

$$\log y_{it} = \beta_0 \log k_{it} + \beta_1 \log m_{it} + \beta_2 \log n_{it} + \lambda \mathbf{X}_{it} + \varepsilon_{it}, \tag{13}$$

[11] These estimates solve the system of equations $0.22 = p^{shock}(1-\bar{\zeta})$ and $0.01 = p^{shock}(1-p^{shock})(1-\bar{\zeta})^2$.

Table 6: Parameter Values

Parameter	Description	Value	Target/Source	Data	Model
β	Discount factor	0.99			
θ	Physical capital share	0.35	See text		
ϕ	Supplier capital share	0.08	See text		
κ	Returns to scale	0.85			
ρ_z	Persistence of idiosyncratic AR(1)	0.90			
σ_z	Std of idiosyncratic AR(1)	0.10			
φ_K	Quadratic adj. cost (k)	0.20	$\sigma[\frac{i_k}{k}]$	0.12	0.14
φ_M	Quadratic adj. cost (m)	0.15	$\sigma[\frac{i_m}{m}]$	0.65	0.50
δ	Depreciation (k)	0.01	$\mathbb{E}[\frac{i_k}{k}]$	0.01	0.01
η	Fraction of wagebill paid in advance	1			
p^{shock}	Probability of disruption shock	0.83	See text		
$\bar{\zeta}$	Average share of surviving s. capital	0.74	See text		

where y_{it} is sales, m_{it} is supplier capital, k_{it} is physical capital, and n_{it} denotes employment. Vector of controls $\mathbf{X}_{it}$ includes an intercept, as well as year-quarter and industry (at NAICS 3-digit) fixed effects.

Table C2 in Appendix reports OLS estimates of Equation (13). We find that the elasticity of sales with respect to supplier capital is statistically significant at 1 percent level across all columns, and is approximately 0.08 in our preferred specification with full set of fixed effects (column (4)). This value is reasonable provided that intermediate inputs account for about 70 percent of the output, and the foreign share of intermediate inputs is about 10 percent. In our quantitative implementation, we proportionately re-scale the obtained estimates such that they are consistent with the returns to scale parameter κ.

Table 6 summarizes the parameter values.

5 Quantitative Results

In this section, we first demonstrate that the model, equipped with a financial friction, accounts for the cross-sectional patterns documented in Section 3. Subsequently, we use the model to quantify the impact of a supply disruption shock on the economy and emphasize the role of adjustment costs on the recovery speed of the aggregate economy in the aftermath of the shock.

5.1 Cross-Sectional Implications

We study the impact of supply chain disruptions on firm-level performance. We simulate a panel of firms from the model and estimate the following specification on the model-simulated data:

$$y_{it} = \beta_0 sd_{it} + \beta_1 sd_{it} \times l_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{14}$$

where the coefficients of interest, β_0 and β_1, measure how the outcome variable responds to the share of supplier capital destroyed at time t, sd_{it}, and how this effect varies with the financial position of the firm. The vector of controls, $\mathbf{X}_{it-1}$, includes an intercept, firm and time fixed effects, lagged (logarithms of) physical and supplier capital, and lagged measure of financial constraint. In the model, we measure financial constraint as the ratio of borrowed funds to cash flow, $l_{it} = \frac{\eta W_t n_{it}}{\pi_{it}}$. In the model, l_{it} is positively associated with productivity and negatively correlated with capital stocks. In other words, capital-poor firms with high productivity are identified as more constrained, as they seek to increase investment to better align their capital stocks with their productivity levels.

We consider four outcome variables: stock returns, revenue (per unit of lagged physical capital), investment in physical and supplier capitals.[12] Table 7 provides the results. The dependent variable is a stock return r_{it} in columns (1) and (2), and revenue in columns

[12]We measure investment in capital as the log difference, which is consistent with how we measured these objects in the data (see Section 3). Stock returns are computed as $r_{it} = \frac{Div_{it} + v(k_{it+1}, m_{it+1}, z_{it+1})}{v(k_{it}, m_{it}, z_{it})}$.

TABLE 7: CROSS-SECTIONAL IMPLICATIONS OF SUPPLY CHAIN DISRUPTIONS: MODEL-SIMULATED DATA

	Returns		Revenue		$\Delta \log m$		$\Delta \log k$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share Disrupted	-0.021	-0.008	-0.031	-0.007	0.461	0.558	-0.010	-0.010
Share Disrupted x FC		-0.465		-0.862		-3.507		-0.059
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.055	0.062	0.351	0.773	0.141	0.155	0.176	0.361

Notes: Table 7 reports OLS estimates of Equation 14. The dependent variable is a stock return (columns (1) and (2)), revenue divided by the lagged value of physical capital (columns (3) and (4)), log change in supplier capital $\Delta \log m_{it+1}$ (columns (5) and (6)) and physical capital $\Delta \log k_{it+1}$ (columns (7) and (8)). $Share\ Disrupted_{it}$ is a fraction of supplier capital got destroyed for firm i at time t; FC_{it} is a measure of financial constraint (ratio of borrowed funds within period to cash flow). The vector of controls, $\mathbf{X}_{it-1}$, includes an intercept, firm and time fixed effects, lagged (logarithms of) physical and supplier capital, and lagged ratio of borrowed funds to cash flow.

(3) and (4). We find that, following a supply disruption shock, firms' returns and revenue decline. This finding is consistent with our empirical results reported in Section 3. The effect is heterogeneous in the cross-section, with both revenue and stock returns declining stronger for more financially constrained firms.

The next two columns (columns (5) and (6)) demonstrate that investment in supplier capital, $\Delta \log m$, increases in response to a supply disruption shock, as firms attempt to restore their supplier capital stock. We illustrate this point further in Section 5.2, where we analyze the aggregate impact of a supply disruption shock. The interaction term in column (6) indicates that more constrained firms experience a weaker surge in investment following a shock. This finding is consistent with the cross-sectional evidence reported in Table 2.

The last two columns show the impact on physical capital investment. The overall effect is negative, although quantitatively small. The size of the effect is commensurate with the share of supplier capital (i.e., the type of capital affected by the shock) in the production function. Overall, the model captures central cross-sectional patterns reported in the empirical part of the paper well.

Financial Constraints Delay Recovery of Supplier Capital We now demonstrate how the financial constraint delays the recovery of supplier capital in the aftermath of a supply disruption shock. To this end, we estimate a series of regressions:

$$\Delta_{t-1}^{t+k} \log m_{it} = \beta_0^k sd_{it} + \beta_1^k sd_{it} \times l_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{15}$$

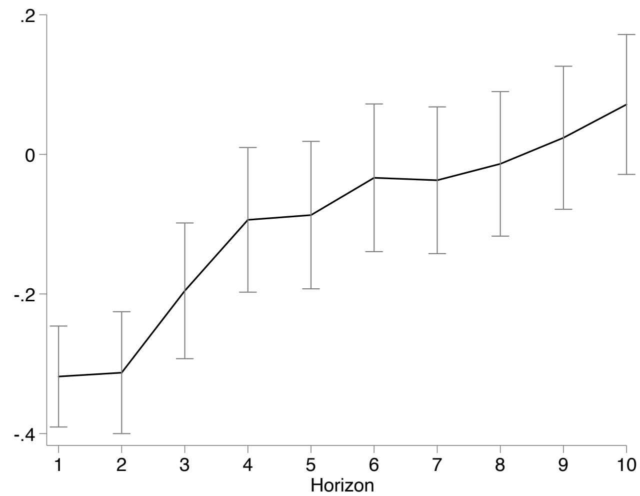
where the horizon $k \in \{1, \ldots, 10\}$. The vector of controls is the same as in Equation (14). In the aftermath of a supply disruption shock, firms restore supplier capital through investment, and $\{\widehat{\beta_0^k}\}_{k=1}^{10}$ converges to zero as k increases. However, more financially constrained firms recover more slowly, as evidenced by the negative interaction terms for the first several periods as shown in Figure 7. The difference in supplier capital stocks (relative to pre-disruption levels) between constrained and unconstrained firms becomes insignificant only four to five quarters after the shock. We interpret this as evidence of a persistent effect of financial constraints on firms' recovery.

We next use our framework to analyze the aggregate impact of a supply disruption shock.

5.2 Impact of Disruption Shock

We consider a perfect foresight (with respect to the aggregate shock ζ_t) transition dynamics whereby firms unexpectedly receive a one-period long increase in the severity of supply disruptions. Specifically, we assume that the economy is at the steady-state at time $t = 0$. At time $t = 1$, firms learn the sequence $\{\zeta_t\}_{t=1}^{T}$ where $\zeta_1 = 0.95\bar{\zeta}$ and $\zeta_t = \bar{\zeta}$ for $t = 2, 3, \ldots$

Figure 7: Financial Constraint Delays Recovery of Supplier Capital



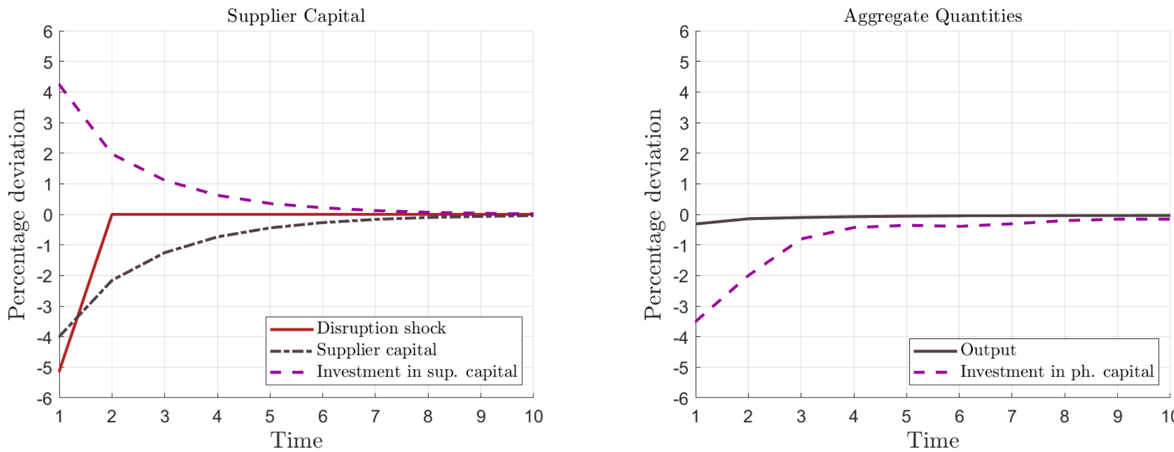
Notes: Figure 7 reports OLS estimates of the interaction term in Equation (15), $\{\widehat{\beta_1^k}\}_{k=1}^{10}$. Vertical intervals denote 90 percent confidence bounds.

That is, a fraction of supplier capital being destroyed increases by five percent for those firms which receive the disruption shock at $t = 1$; this accords well with three percentage point increase in the share of established trade pairs being disrupted over the last several years as reported in Figure 3. We trace the transition of economy back to the steady-state in the aftermath of the supply disruption shock. Computational details of this exercise are relegated to Appendix B.3.

Figure 8 reports the results. Upon impact at $t = 1$, aggregate supplier capital declines by four percent relative to the steady-state; at the same time, firms start actively investing into supplier capital as reflected by a four percent increase in aggregate investment i_m. It takes the economy about ten quarters to fully recover from the disruption shock which lasted one quarter.

The right panel demonstrates that aggregate output drops by 0.3 percent upon impact. Aggregate investment into physical capital declines by 3.5 percent, reflecting complementar-

Figure 8: Impact of Supply Disruption Shock



(A) Supplier capital (B) Aggregate quantities

Notes: Figure 8 reports results for the perfect foresight transition dynamics exercise as described in Section 5.2. Time $t = 0$ corresponds to the steady-state, and firms learn a sequence of shocks $\{\zeta_t\}_{t=1}^{T}$ at $t = 1$.

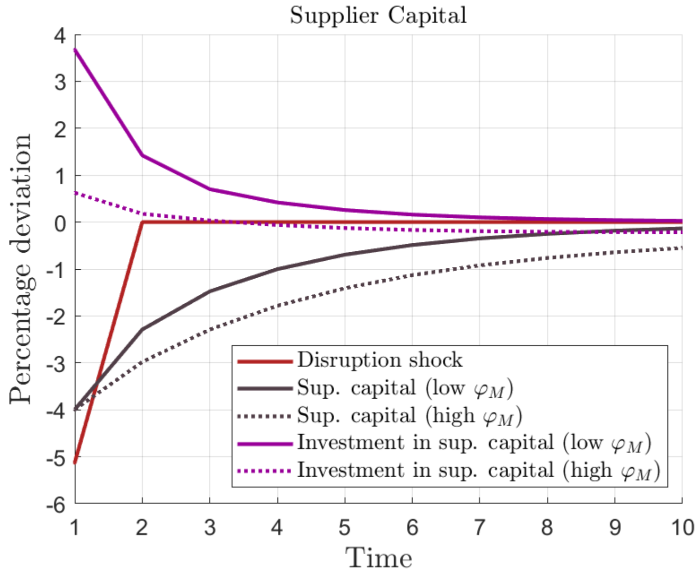
ity of the two types of capital in the production technology. As the economy transitions back, physical capital investment rises to bring the aggregate capital stock back to the steady-state level.

5.3 Investment in Supplier Capital as an Endogenous Margin of Adjustment

Firms in our model, upon receiving a supply disruption shock, can adjust by increasing their investment into supplier capital. Thus, adjustment costs govern the firms' ability to respond to shocks. In the limit when $\varphi_M \to \infty$, scarring effect of disruptions becomes permanent, as firms are unable to increase their capital stocks.

We now demonstrate quantitatively that firms' ability to adjust to supply disruption shocks plays a key role, as higher costs can substantially delay recovery. To illustrate this, we increase the parameter φ_M from 0.3 to 3 and repeat the transition dynamics exercise

Figure 9: Impact of Supply Disruption Shock: Role of Adjustment Costs



Notes: Figure 9 reports results for the perfect foresight transition dynamics exercise as described in Section 5.2. Time $t = 0$ corresponds to the steady-state, and firms learn a sequence of shocks $\{\zeta_t\}_{t=1}^T$ at $t = 1$. Solid lines correspond to the parameterized value of φ_M, dotted lines correspond to the model with a tenfold larger value of φ_M.

described above. Figure 9 compares the dynamics of aggregate supplier capital and investment in supplier capital along the transition path for the two values of φ_M. We find that with higher adjustment costs, investment in m only increases by 0.6 percent upon impact—merely 20 percent of the effect observed in the baseline scenario. Aggregate supplier capital declines by the same percentage in both economies, but it takes about four quarters longer for an economy to recover. Therefore, we conclude that the inability of firms to adjust their supplier capital plays a central role in prolonging the effects of supply disruptions in the aggregate.

6 Conclusion

We use detailed shipment-level data on U.S. seaborne imports to document key facts about supplier capital and supply chain disruptions. We develop a general equilibrium model with heterogeneous firms that invest in both physical and supplier capital. The model accounts for the cross-sectional patterns observed in the data. Firms' ability to accumulate supplier capital through costly investment represents an important endogenous margin of adjustment following supply chain disruptions. We find that restricting this ability by assuming counterfactually high adjustment costs can substantially delay recovery.

Acknowledgements

We thank Viral Acharya, Steven Berry, Job Boerma, Matt Elliott, Kinda Hachem, Amit Khandelwal, Giuseppe Moscarini, Oleg Itskhoki, Michael Peters, Lawrence Schmidt, Peter Schott, Jesse Schreger, Gill Segal, Alireza Tahbaz-Salehi, David Wilkinson, Fabrizio Zilibotti for useful comments and Tobin Center for Economic Policy for support. This paper subsumes the results on the supply chain disruptions in "Macroeconomic and Asset Pricing Effects of Supply Chain Disasters" (Smirnyagin and Tsyvinski, 2022).

References

Acemoglu, Daron and Alireza Tahbaz-Salehi, "The Macroeconomics of Supply Chain Disruptions," *Review of Economic Studies*, Forthcoming.

Acharya, Viral, Matteo Crosignani, Tim Eisert, and Christian Eufinger, "How Do Supply Shocks to Inflation Generalize? Evidence from the Pandemic Era in Europe," *NBER Working Paper 31790*, 2023.

Alessandria, George, Shafaat Yar Khan, Armen Khederlarian, Carter Mix, and Kim Ruhl, "The Aggregate Effects of Global and Local Supply Chain Disruptions: 2020-2022," *Journal of International Economics*, 2023.

Ambrus, Attila and Matt Elliott, "Investments in Social Ties, Risk Sharing, and Inequality," *Review of Economic Studies*, 2021, *88*, 1624–1664.

Amiti, Mary, Oleg Itskhoki, and David Weinstein, "Global Supply Chains and U.S. Import Price Inflation," *SSRN working paper 4747437*, 2024.

Atkeson, Andrew and Patrick Kehoe, "Modeling and Measuring Organizational Capital," *Journal of Political Economy*, 2005, *113*, 1026–1053.

Bai, Hang, Erica Li, Chen Xue, and Lu Zhang, "Asymmetric Investment Rates," *NBER Working Paper 29957*, 2022.

Bai, Xiwen, Jesús Fernández-Villaverde, Yiliang Li, and Francesco Zanetti, "The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory," *NBER Working Paper*, 2024.

Benigno, Gianluca, Julian di Giovanni, Jan Groen, and Adam Noble, "A New Barometer of Global Supply Chain Pressures," *Federal Reserve Bank of New York Staff Reports, no. 1017*, 2022.

Bhandari, Anmol and Ellen McGrattan, "Sweat Equity in U.S. Private Business," *Quarterly Journal of Economics*, 2021, *136*, 727–781.

Bils, Mark, "Pricing in a Customer Market," *Quarterly Journal of Economics*, 1989, *104*, 699–718.

Blaum, Joaquin, Federico Esposito, and Sebastian Heise, "Input Sourcing under Supply Chain Risk: Evidence from U.S. Manufacturing Firms," *Working Paper*, 2023.

Bonadio, Barthélémy, Zhen Huo, Andrei Levchenko, and Nitya Pandalai-Nayar, "Global Supply Chains in the Pandemic," *Journal of International Economics*, 2021, *133*, 1–23.

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

Castro-Vincenzi, Juanma, Gaurav Khanna, Nicolas Morales, and Nitya Pandalai-Nayar, "Weathering the Storm: Supply Chains and Climate Risk," *NBER Working Paper 32218*, 2024.

Comin, Diego, Robert Johnson, and Callum Jones, "Supply Chain Constraints and Inflation," *NBER Working Paper 31179*, 2023.

Cooper, Russell and John Haltiwanger, "On the Nature of Capital Adjustment Costs," *Review of Economic Studies*, 2006, *73*, 611–633.

Crouzet, Nicolas, Janice Eberly, Andrea Eisfeldt, and Dimitris Papanikolaou, "A Model of Intangible Capital," *NBER Working Paper 30376*, 2022.

Duval, Romain, Gee Hee Hong, and Yannick Timmer, "Financial Frictions and the Great Productivity Slowdown," *Review of Financial Studies*, 2020, *33*, 475–503.

Eisfeldt, Andrea and Dimitris Papanikolaou, "Organizational Capital and the Cross-Section of Expected Returns," *Journal of Finance*, 2013, *68*, 1365–1406.

_ and _ , "The Value and Ownership of Intangible Capital," *American Economic Review: Papers & Proceedings*, 2014, *104*, 189–194.

Elliott, Matthew, Benjamin Golub, and Matthew Jackson, "Financial Networks and Contagion," *American Economic Review*, 2014, *104*, 3115–3153.

_ , _ , and Matthew Leduc, "Supply Network Formation and Fragility," *American Economic Review*, 2022, *112*, 2701–2747.

Flaaen, Aaron, Flora Haberkorn, Logan Lewis, Anderson Monken, Justin Pierce, Rosemary Rhodes, and Madeleine Yi, "Bill of Lading Data in International Trade Research with an Application to the COVID-19 Pandemic," *Finance and Economics Discussion Series 2021-066. Washington: Board of Governors of the Federal Reserve System*, 2021.

Gomes, Joao, "Financing Investment," *American Economic Review*, 2001, *91*, 1263–1285.

Gourio, Francois and Leena Rudanko, "Customer Capital," *Review of Economic Studies*, 2014, *81*, 1102–1136.

Heise, Sebastian, "Essays in Macroeconomics and International Trade," *Yale University ProQuest Dissertations & Theses*, 2016.

_ , Justin Pierce, Georg Schaur, and Peter Schott, "Tariff Rate Uncertainty and the Structure of Supply Chains," *NBER Working Paper 32138*, 2024.

Hennessy, Christopher and Toni Whited, "How Costly Is External Financing? Evidence from a Structural Estimation," *Journal of Finance*, 2007, *62*, 1705–1745.

Jain, Nitish and Di Wu, "Can Global Sourcing Strategy Predict Stock Returns?," *Manufacturing and Service Operations Management*, 2023, *25*, 1357–1375.

—, Karan Girotra, and Serguei Netessine, "Managing Global Sourcing: Inventory Performance," *Management Science*, 2013, *60*, 1202–1222.

—, —, and —, "Recovering Global Supply Chains from Sourcing Interruptions: The Role of Sourcing Strategy," *Manufacturing and Service Operations Management*, 2021, *24*, 846–863.

Kaplan, Steven and Luigi Zingales, "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?," *Quarterly Journal of Economics*, 1997, *112*, 169–215.

Khan, Aubhik and Julia Thomas, "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics," *Econometrica*, 2008, *76*, 395–436.

Krause, Daniel, Robert Handfield, and Beverly Tyler, "The Relationships Between Supplier Development, Commitment, Social Capital Accumulation and Performance Improvement," *Journal of Operations Management*, 2007, *25*, 528–545.

Leenders, Michael, "Supplier Development," *Journal of Purchasing*, 1966, *2*, 47–62.

Liu, Ernest, Vladimir Smirnyagin, and Aleh Tsyvinski, "Supply Disruptions Index (SDI): Data and Methodology," *SSRN working paper 4430231*, 2023.

McGrattan, Ellen, "Intangible Capital and Measured Productivity," *Review of Economic Dynamics*, 2020, *37*, S147–S166.

Miranda, Mario and Paul Fackler, "Applied Computational Economics and Finance," *MIT Press*, 2002.

Moyen, Nathalie, "Investment–Cash Flow Sensitivities: Constrained versus Unconstrained Firms," *Journal of Finance*, 2005, *59*, 2061–2092.

Neumeyer, Pablo and Fabrizio Perri, "Business Cycles in Emerging Economies: The Role of Interest Rates," *Journal of Monetary Economics*, 2005, *52*, 345–380.

Ostrovsky, Michael, "Stability in Supply Chain Networks," *American Economic Review*, 2008, *98*, 897–923.

Ottonello, Pablo and Thomas Winberry, "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 2020, *88*, 2473–2502.

Paciello, Luigi, Andrea Pozzi, and Nicholas Trachter, "Price Dynamics with Customer Markets," *International Economic Review*, 2019, *60*, 413–446.

Rotemberg, Julio and Michael Woodford, "Markups and the Business Cycle," *NBER Macroeconomics Annual*, 1991, *6*, 63–129.

Sedláček, Petr and Vincent Sterk, "The Growth Potential of Startups over the Business Cycle," *American Economic Review*, 2017, *107*, 3182–3210.

Villena, Verónica, Elena Revilla, and Thomas Choi, "The Dark Side of Buyer–Supplier Relationships: A Social Capital Perspective," *Journal of Operations Management*, 2011, *29*, 561–576.

White House, "The Biden-Harris Plan to Revitalize American Manufacturing and Secure Critical Supply Chains 2022," 2022.

_ , "Issue Brief: Supply Chain Resilience," 2023.

Whited, Toni and Guojun Wu, "Financial Constraints Risk," *Review of Financial Studies*, 2006, *19*, 531–559.

Winberry, Thomas, "Lumpy Investment, Business Cycles, and Stimulus Policy," *American Economic Review*, 2021, *111*, 364–396.

Xu, Qiping and Taehyun Kim, "Financial Constraints and Corporate Environmental Policies," *Review of Financial Studies*, 2022, *35*, 576–635.

Young, Eric, "Solving the Incomplete Markets Model with Aggregate Uncertainty Using the Krusell-Smith Algorithm and Non-Stochastic Simulations," *Journal of Economic Dynamics and Control*, 2010, *34*, 36–41.

Online Appendix

"Supply Chain Disruptions and Supplier Capital in U.S. Firms"

by Ernest Liu, Yukun Liu, Vladimir Smirnyagin and Aleh Tsyvinski

Table of Contents for Appendix

Appendix A: Empirical Appendix

A.1 Measuring Supplier Concentration and Relationship Strength

Supplier Concentration Following Jain and Wu (2023), we measure supplier concentration of firm i in quarter t as a weighted average of concentration in its set of suppliers across all imported HS-2 product categories. For a given product code c, we measure supplier concentration using the Herfindahl index:

$$HHI_{itc} = \sum_{j=1}^{NS_{itc}} (IV_{itcj}/IV_{itc})^2, \tag{A.1}$$

where NS_{itc} is the total number of suppliers from whom product category c is sourced by firm i at time t, IV_{itcj} is the total monetary value of imports (in deflated U.S. dollars) by firm i from supplier j in category c, and IV_{itc} is the total monetary value of imports under product category c.

We then aggregate product-specific concentration indices using category-specific import volumes IV_{itc} as weights:

$$SC_{it} = \frac{\sum_{c=1}^{NC_{it}} IV_{itc} \times HHI_{itc}}{\sum_{c=1}^{NC_{it}} IV_{itc}}, \tag{A.2}$$

where NC_{it} is the total number of product categories imported by firm i in quarter t.

Relationship Strength Following Jain et al. (2021) and Jain and Wu (2023), we measure relationship strength of firm i with its suppliers in year t as a weighted average of repeat business intensity (RBI) with suppliers across HS-2 product categories. In a given year t, the repeat business intensity between firm i and a supplier j is the ratio of the number of months in that year in which product category c is sourced from supplier j to the total number of months in that year in which category c is sourced from any supplier:

$$RBI_{itc} = \frac{1}{NS_{itc}} \sum_{j=1}^{NS_{itc}} \frac{\text{Count of non-zero sup. months}_{ijtc}}{\text{Count of non-zero months}_{itc}}, \tag{A.3}$$

where NS_{itc} is the total number of suppliers from which category c is imported by firm i in year t. We set weights for repeat business intensity in category c to the total (deflated) value of imports in that category made by firm i in year t:

$$RS_{it} = \frac{\sum_{c=1}^{NC_{it}} IV_{itc} \times RBI_{itc}}{\sum_{c=1}^{NC_{it}} IV_{itc}}. \tag{A.4}$$

A.2 Investment into Supplier and Physical Capital: IV Regressions

In order to alleviate the impact of demand effects, we provide estimates for a number of IV regressions. On a conceptual level, our instrument is based on the number of U.S. firms with which the established foreign shippers of a given U.S. firm trade in a given time period, excluding the focal U.S. firm. We conduct these calculations at the firm level within each product category and subsequently aggregate them to the firm-quarter level using firm import values at the product level as weights. Intuitively, this instrument is designed to capture the notion that when a given established trade pair is inactive, and this is concurrent with a drop in activity among that U.S. firm's established shippers, it is likely that the inactivity is driven by supply considerations rather than a decline in the given firm's demand.

Specifically, for each U.S. firm i we compute the total number of *other* U.S. consignees within product category j with which established shippers of firm i are trading with at time t, B_{ijt}:

$$B_{ijt} = \sum_{s \in \mathcal{S}_{ijt}} [|\mathcal{AC}_{st}| - \mathbf{1}_{\{(i,s) \text{ active at } t\}}], \tag{A.5}$$

where $\mathcal{S}_{ijt}$ is the set of established shippers of firm i at time t within the product category j, and $\mathcal{AC}_{st}$ is the set of active established customers of foreign shipper s at time t, from which we exclude the focal firm i if it is trading with firm s at time t.

The leave-one-out instrument is then given by:

$$\text{Index (other)}_{it} = \sum_{j \in \mathcal{N}_{it}} W_{ijt} B_{ijt}, \tag{A.6}$$

where $\mathcal{N}_{it}$ is the set of product categories firm i imported at time t, and W_{ijt} is the import share of the total import value of firm i accounted for by product category j at time t. Finally, we average the instrument at the industry-quarter level.

For convenience, Table A1 provides IV estimates along with OLS estimates reported in the main text (see Table 2). According to column 1, the effect of disruptions on investment in supplier capital accumulation is positive, although not statistically significant. The point estimate suggests that a one standard deviation increase in the index is associated with about a 0.5pp increase in the investment rate $\Delta \log m_{it+1}$. Column 2 reveals substantial heterogeneity in responsiveness to supply disruption shocks across firms. The interaction term with firm leverage is negative and statistically significant at the 1 percent level. The estimates indicate that a one standard deviation increase in the supply disruptions index for firms with a 10pp higher leverage is associated with 0.4pp lower investment rate. This result highlights that the positive average effect reported in column 1 masks a significantly weaker response from leveraged firms.

In columns 3-4, we report IV estimates using (A.6) as an instrument. Qualitatively, the estimates remain similar, but they become larger in absolute value. For example, the interaction term in column 4 suggests that a one standard deviation increase in the supply disruptions index for firms with 10 percentage points higher leverage is associated with a 1.9 percentage point lower investment rate—an effect which is nearly four times larger than the OLS estimates reported in column 2.

In columns (5)-(8), we study the impact of supply disruption shocks on firms' investment over a two-quarter horizon. Overall, the estimates increase in magnitude at this longer horizon, and in some cases, statistical significance also increases. We interpret this as a reflection of the dynamic nature of investment decisions and the persistent role of financial conditions in shaping future investment choices.

A.3 Additional Empirical Results

Table A1: Supply Chain Disruptions and Firm Investment in Supplier Capital: OLS and IV Estimates

	$\Delta_t^{t+1}\log m$				$\Delta_t^{t+2}\log m$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index	0.0052	0.0165**	0.1977*	0.2356*	0.0060	0.0294**	0.4095*	0.4454**
	(0.005)	(0.007)	(0.118)	(0.121)	(0.009)	(0.013)	(0.216)	(0.217)
Index x FC		-0.0444***		-0.1929**		-0.0848***		-0.3997***
		(0.016)		(0.077)		(0.030)		(0.140)
FC		-0.0511**		-0.0466*		-0.1242***		-0.1168**
		(0.025)		(0.028)		(0.048)		(0.052)
IV	No	No	Yes	Yes	No	No	Yes	Yes
F(index)			16.5	15.7			17.2	16.0
F(index x FC)				66.9				71.0
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.072	0.074			0.116	0.119		
N	33250	32034	33241	32025	32469	31297	32460	31288

Notes: Table A1 reports OLS and IV estimates of Equation 4. The dependent variable is investment rate into supplier capital $\Delta_t^{t+k}\log m_{it+1}$ where $k \in \{1,2\}$. *Index* is a (standardized) firm-level index of supply chain disruptions constructed in Section 2.3; *FC* is a lagged value of firm's leverage. The vector of controls includes year-quarter and firm fixed effects, a standardized, lagged measure of supplier concentration, a standardized, lagged measure of relationship strength, as well as a standardized, lagged inventory-to-sales ratio. Standard errors are clustered at the firm level. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

Supply Disruptions and Investment into Physical Capital Table A2 presents results for investment in physical capital. The coefficient on the supply disruptions index is negative and statistically significant at the 5 percent level. The point estimate suggests that a one standard deviation increase in the index is associated with a 0.2 percentage point decline in the physical capital investment rate. The interaction with firm leverage is also negative, though it is quantitatively small and statistically significant at the 10 percent level only.

The IV estimates in columns (3)-(4) indicate that the overall effect of supply chain disruptions on physical capital investment is muted in the aggregate; however, the interaction term with financial conditions is statistically significant at the 1 percent level (though it is quantitatively small compared to the case of supplier capital investment reported in Table 2). Results over a longer horizon in columns (5)-(8) are quantitatively more pronounced but remain qualitatively similar.

Table A2: Supply Chain Disruptions and Firm Investment in Physical Capital

	$\Delta_t^{t+1}\log m$				$\Delta_t^{t+2}\log m$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index	-0.0017**	-0.0003	-0.0043	-0.0138	-0.0056***	-0.0021	-0.0443	-0.0659
	(0.001)	(0.001)	(0.017)	(0.018)	(0.002)	(0.003)	(0.044)	(0.048)
Index x FC		-0.0050*		-0.0400***		-0.0130*		-0.0857**
		(0.003)		(0.013)		(0.007)		(0.034)
FC		-0.0408***		-0.0410***		-0.0725***		-0.0745***
		(0.006)		(0.006)		(0.017)		(0.017)
IV	No	No	Yes	Yes	No	No	Yes	Yes
F(index)			16.3	15.4			17.0	15.8
F(index x FC)				69.7				74.0
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.172	0.177			0.222	0.228		
N	33338	32114	33329	32105	32589	31408	32580	31399

Notes: Table A2 reports OLS and IV estimates of Equation 4. The dependent variable is investment rate into physical capital $\Delta_t^{t+k}\log m_{it+1}$ where $k \in \{1,2\}$. *Index* is a (standardized) firm-level index of supply chain disruptions constructed in Section 2.3; *FC* is a lagged value of firm's leverage. The vector of controls includes year-quarter and firm fixed effects, a standardized, lagged measure of supplier concentration, a standardized, lagged measure of relationship strength, as well as a standardized, lagged inventory-to-sales ratio. Standard errors are clustered at the firm level. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

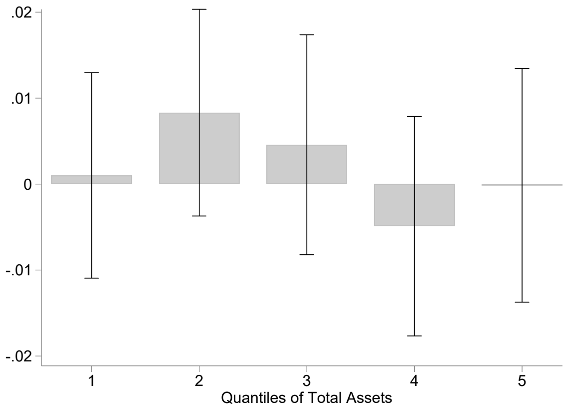
Firm Size and Investment into Supplier and Physical Capital Do larger firms invest more in supplier capital? To investigate this, we group observations into five quantiles based on total assets and report the average investment rate in each bin. Panel (A) of Figure A1 shows that there is no strong connection between firm size and investment in supplier capital; the 95 percent confidence intervals overlap across all five size groups.

Patterns are very different in the case of investment into physical capital, as evidenced by Panel (B). The smallest firms tend to exhibit the highest investment rates (with an average of 1 percent); the average rate monotonically declines, reaching 0.4 percent for the largest 20 percent of firms.

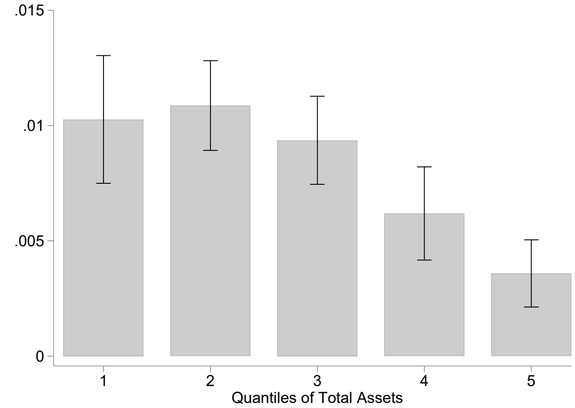
Panels (C) and (D) show that investment rates are monotonically declining in their respective capital stocks.

Heterogeneity in Supplier Capital and Exposure to Supply Chain Disruptions Across Industries Panel (A) of Figure A2 shows significant variation in supplier capital

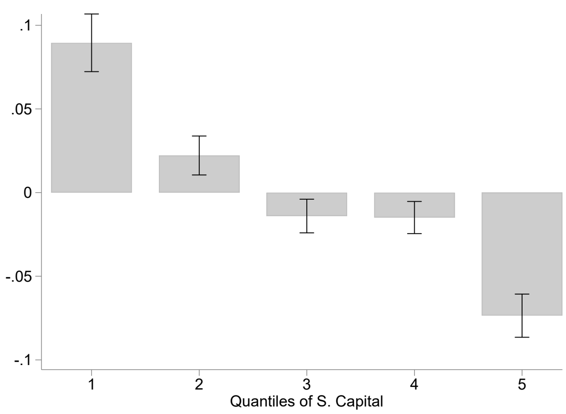
Figure A1: Average Investment Rates and Firm Size



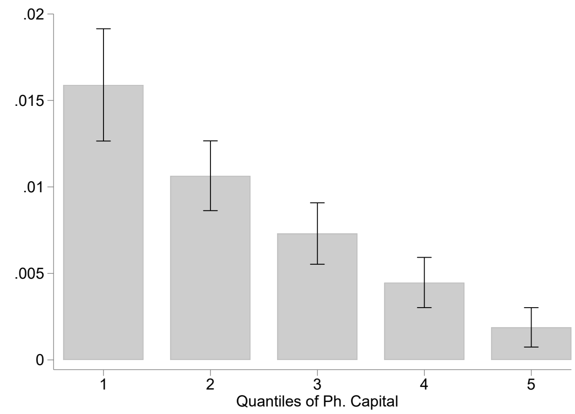
(A) Investment in supplier capital by assets



(B) Investment in physical capital by assets



(C) Investment in supplier capital by s. capital



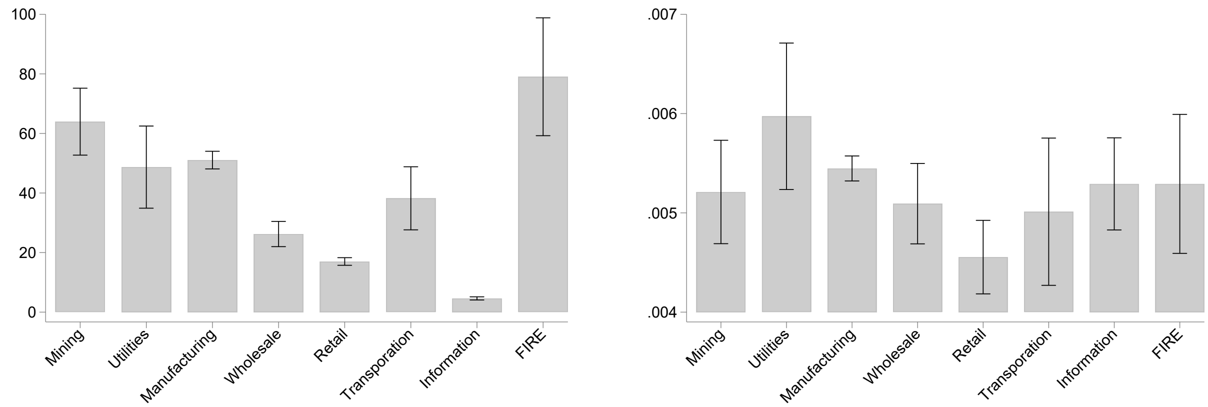
(D) Investment in physical capital by ph. capital

Notes: Figure A1 consists of 2 panels. Panel (A) plots the mean investment rate into supplier capital across firm size quantiles (total assets); Panel (B) plots the mean investment rate into physical capital. Vertical intervals represent 95 percent confidence bounds.

across industries. Retail and information firms, on average, have the smallest amount of supplier capital. In contrast, manufacturing, mining, and FIRE firms are at the other end of the spectrum, with the largest amount of supplier capital. This finding suggests that firms in different sectors operate differently; for example, while retail and wholesale firms import a significant volume of goods by sea, they tend to work with a large number of suppliers, of which relatively few are considered "permanent" (or established, using our terminology).

Panel (B) shows that despite pronounced variation in supplier capital, industries have similar exposure to supply disruption shocks.

Figure A2: Supplier Capital and Supply Disruptions by NAICS 2-Digit Industry



(A) Supplier capital (B) Supply disruption rate

Notes: Figure A2 consists of 2 panels. Panel (A) plots the mean supplier capital by NAICS 2-digit industry; Panel (B) plots the mean disruption rate by industry. Vertical intervals represent 95 percent confidence bounds.

A.4 Definitions of Financial Variables

Variable names in parentheses correspond to the Compustat item names.

- **Leverage** = (Long-term debt (`dlttq`) + Debt in current liabilities (`dlcq`))/Total assets (`atq`);
- **Cash Flow** = Operating income before depreciation (`oibdq`) /Total assets (`atq`);
- **Long-term debt** = Long-term debt (`dlttq`)/Total assets (`atq`);
- **Size** = Logarithm of total assets (`atq`);
- **Dividend dummy** = Dividends (`dvpq`) > 0;
- **Industry sales growth** = Change in the logarithm of total sales at NAICS 3-digit level;
- **Sales growth** = Change in the logarithm of sales (`saleq`) at the firm level;

– Whited and Wu (2006) **Index** = –0.091***Cash flow** + 0.062***Dividend dummy** + 0.021***Long-term debt** – 0.044***Size** + 0.102***Industry sales growth** – 0.035***Sales growth**;

– **Payout ratio** = (Cash dividends (`dvp+dvc`) + Repurchases (`prstkc`))/Income before extraordinary items (`ib`);

Appendix B: Model Appendix

B.1 Definition of Equilibrium

The Recursive Competitive Stationary Equilibrium for this economy consists of the following functions and objects:

$$\left\{v, v^{cont}, n, k', m', W, R, H, C, B, \Xi, \mu\right\},$$

such that:

1. H solves the household's problem (11)-(12) and $\{C, B, \Xi\}$ are the corresponding policy functions,
2. $\{v, v^{cont}\}$ solve the firm's problem (6)-(10), and $\{n, k', m'\}$ are the corresponding policy functions,
3. labor market clears

   $$\int n(k, m, z)\mathrm{d}\mu = 1,$$

   where μ is the stationary distribution of firms across idiosyncratic productivity z and capital stocks k and m;
4. bonds market clears (by Walras law):

   $$B = \int \eta W n \mathrm{d}\mu,$$

   and the risk-free rate is given by $R_t = \frac{U'(t)}{\beta U'(t+1)}$ (which is $1/\beta$ at the steady-state);
5. goods market clears:

   $$\int y(k, m, z, n)\mathrm{d}\mu = C + I_K + I_M + AC_K + AC_M,$$

where (for $x \in \{k, m\}$):

$$I_x = \int i_x(k, m, z) \mathrm{d}\mu$$
$$AC_x = \int \frac{\varphi_x}{2} \left(\frac{x'(k, m, z) - x}{x} \right)^2 x \mathrm{d}\mu$$

6. the distribution of firms μ is induced by decision rules $k'(k, m, z)$ and $m'(k, m, z)$, and the exogenous evolution of idiosyncratic productivity z (Equation 5);

7. household's decision Ξ is consistent with the stationary distribution of firms μ.

B.2 Computation Algorithm: Steady-State

We use collocation methods to solve the firm's functional equations. In practice, we use Chebyshev polynomials to approximate value functions.

We set up a grid of collocation nodes $\mathcal{K} \times \mathcal{M} \times \mathcal{Z}$, with N_i nodes in each dimension, $i \in \{\mathcal{K}, \mathcal{M}, \mathcal{Z}\}$. The computation of the stationary state of the model proceeds in the following 4 steps:

1. guess the equilibrium wage rate, W;

2. solve for individual decision rules k' and m';

3. given the decision rules, compute stationary histogram (distribution of firms over the state space);

4. compute the excess demand on the labor market. If it exceeds some prespecified tolerance, adjust the wage guess correspondingly and go back to Step 2. Otherwise, terminate.

B.2.1 Approximation of Value Functions

We approximate value functions: $V(\cdot)$, normalized by the household's marginal utility. We represent this value function as a weighted sum of orthogonal polynomials:

$$V(k,m,z) = \sum_{a,b,c=1,1,1}^{N_{\mathcal{K}},N_{\mathcal{M}},N_{\mathcal{Z}}} \theta^{abc} T^a(k) T^b(m) T^c(z) \tag{B.1}$$

where $\mathbf{\Theta} = \{\theta^{a,b,c}\}$ are approximation coefficients, and $T^i(\cdot)$ is the Chebyshev polynomial of order i.

We use a collocation method to simultaneously solve for $\mathbf{\Theta}$. Collocation method requires setting the residual equation to hold exactly at $N = N_{\mathcal{K}} \times N_{\mathcal{M}} \times N_{\mathcal{Z}}$ points ; therefore, we essentially solve for N unknown coefficients. We compute the basis matrices for Chebyshev polynomials using Miranda and Fackler (2002) Compecon toolbox. Subsequently, we solve for a vector of unknown coefficients using Newton's method. A much slower alternative is to iterate on the value function. Given the current guess of coefficients, we solve for the optimal policy $k'(k,m,z)$ and $m'(k,m,z)$ using vectorized golden search. After we solve for the policy function, we recompute decision rules on a finer grid, and, subsequently, compute the stationary distribution.

B.2.2 Stationary Distribution

When we solve for a stationary distribution, we iterate on a mapping using firms' decisions rules:

$$L' = \mathbf{Q}' L,$$

where L is a current distribution of firms across the state space. Matrix $\mathbf{Q}$ is a transition matrix, which determines how mass of firms shifts in the (k,m,z)-space. It is a direct product of three transition matrices $\mathbf{Q}_k$. $\mathbf{Q}_m$, and $\mathbf{Q}_z$:

$$\mathbf{Q} = \mathbf{Q}_k \odot \mathbf{Q}_m \odot \mathbf{Q}_z,$$

which govern the shift of mass along k-, m-, and z-dimensions, respectively. While $\mathbf{Q}_z$ is completely determined by the exogenous stochastic process, matrix $\mathbf{Q}_k$ and matrix $\mathbf{Q}_m$ is constructed so that the model generates an unbiased distribution in terms of aggregates.[13] More precisely, element (i, j) of the transition matrix $\mathbf{Q}_k$ informs which fraction of firms with the current idiosyncratic state k_i will end up having k_j tomorrow. Therefore, this entry of the matrix is computed as:

$$\mathbf{Q}_k(i,j) = \left[\mathbf{1}_{k' \in [k_{j-1},k_j]} \frac{k' - k_j}{k_j - k_{j-1}} + \mathbf{1}_{k' \in [k_j,k_{j+1}]} \frac{k_{j+1} - k'}{k_{j+1} - k_j}\right].$$

We similarly construct the matrix $\mathbf{Q}_m$.

Tensor product of matrices $\mathbf{Q}_k$, $\mathbf{Q}_m$ and $\mathbf{Q}_z$ is computed using the `dprod` function from the Miranda and Fackler (2002) toolkit.

B.3 Computation Algorithm: Transition Dynamics

In this section, we outline an algorithm for computing transition dynamics. In the paper, we study the impact of an unexpected shock ζ_t and the subsequent perfect foresight transition of the economy back to the steady state.

1. Compute the steady-state for the initial period (T_{start}); that is, firms solve their problems believing that the supply disruption shock ζ_t will stay at the steady-state level indefinitely;

2. Consider a transition horizon T. The horizon should be large enough to ensure that the economy converges back to the steady-state by time T;

3. We assume that firms learn the series of shocks $\{\zeta_t\}_{t=1}^{T}$ at time $t = 1$. All elements of this sequence of shocks are equal to the steady-state level, but one: there is a surprise disruption shock at $t = 1$;

4. Guess a sequence of wages $\{\widehat{W}_t\}_{t=1}^{T-1}$ and marginal utilities $\{\widehat{MU}_t\}_{t=1}^{T-1}$;

[13] See Young (2010) for more details.

5. Given that we know the value function in the terminal period T, $\tilde{v}_T$, we can solve for the optimal intertemporal decisions in $t = T-1$:

$$\{\widehat{k';m'}\}_{T-1}(k,m,z) = \arg\max_{k',m' \geq 0} \left(\widehat{MU}_{T-1} \times (-i_k - i_m) + \beta \mathbb{E}_t \tilde{v}_T(k',m',z') \right).$$

   Note that we are using value functions scaled by the marginal utility: $\tilde{v}_t = \widehat{MU}_t \times v_t$. We also recover the value function $\tilde{v}_{T-1}$ that corresponds to the obtained decision rules. Value function $\tilde{v}_{T-1}$ is then:

$$\tilde{v}_{T-1}(k,m,z) = p^{shock}\tilde{v}^{cont}_{T-1}(k,\zeta_t m,z) + (1-p^{shock})\tilde{v}^{cont}_{T-1}(k,m,z).$$

   Flow profits $\pi_{T-1}(k,m,z)$ are calculated assuming that the wage rate is $\widehat{W}_{T-1}$;

6. Solving backwards (i.e., by repeatedly executing the previous step), we can recover the entire path of decision rules for $t = 1, \ldots, T-1$;

7. Take the steady-state distribution for period $t = 0$. Apply the recovered sequence of decision rules, $\{\widehat{k',m'}_t(k,m,z)\}_{t=0}^{T-1}$, to compute the evolution of the cross-sectional distribution over the entire transition horizon;

8. Compute excess demand functions on the labor market, and the deviation of the implied sequence of marginal utilities from the guessed one;

9. If the norm of deviations taken across time is sufficiently small, terminate. Otherwise, update the guess of wages and marginal utilities and go back to step (4).

Appendix C: Tables and Figures

Table C1: Key Variables

Variable	Description
panjivarecordid	Unique shipment ID
arrivaldate	Day of arrival
conname	Consignee name
shpname	Shipper name
volumeteu	Volume of shipment in TEUs
conpanjivaid	Consignee ID
shppanjivaid	Shipper ID
hscode	6-digit HS code
companyid	Capital IQ company ID
constateregion	Location (state) of consignee
weightt	Weight of shipment in metric tons
portoflading	Port where shipment was loaded
portofunlading	U.S. port where cleared customs
vessel	Name of vessel
valueofgoodsUSD	Value of shipments in U.S. dollars
shpcountry	Shipper's country

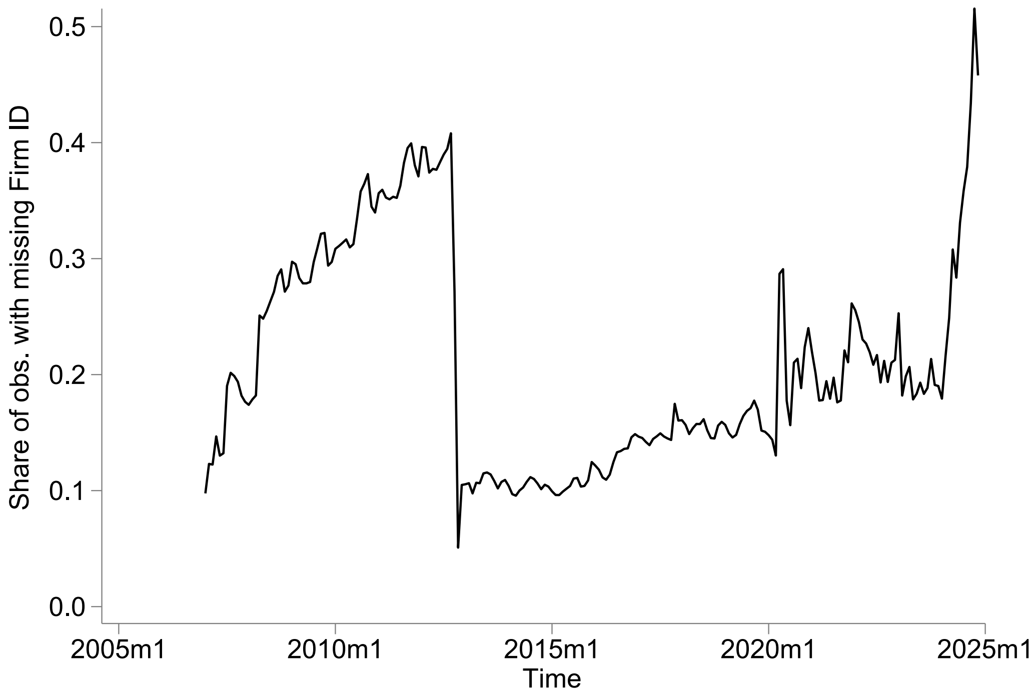
Notes: Table C1 provides a list of key variables in S&P Panjiva data.

TABLE C2: PRODUCTION FUNCTION ESTIMATES

	(1)	(2)	(3)	(4)
Capital	0.3446***	0.3456***	0.3388***	0.3412***
	(0.004)	(0.004)	(0.005)	(0.005)
S. capital	0.1057***	0.1059***	0.0814***	0.0812***
	(0.003)	(0.003)	(0.003)	(0.003)
Employment	0.5326***	0.5314***	0.5594***	0.5571***
	(0.005)	(0.005)	(0.006)	(0.006)
Year-Quarter FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
R^2	0.864	0.866	0.906	0.907
N	25928	25928	25928	25928

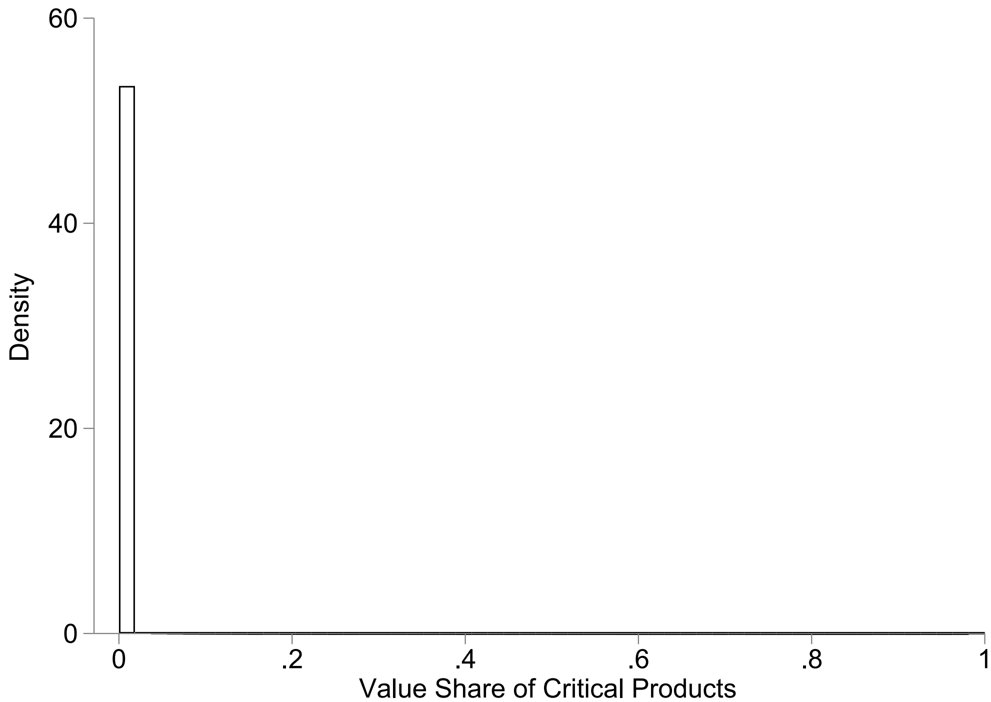
Notes: Table C2 reports OLS estimates of the following equation: $\log y_{it} = \beta_0 \log k_{it} + \beta_1 \log m_{it} + \beta_2 \log n_{it} + \lambda \mathbf{X}_{it} + \varepsilon_{it}$, where the dependent variable y_{it} is sales, m_{it} is supplier capital, k_{it} is physical capital, and n_{it} denotes employment. Vector of controls $\mathbf{X}_{it}$ includes an intercept, as well as year-quarter and industry (at NAICS 3-digit) fixed effects. Underlying sample is restricted to firm-quarter observations with at least 1 million USD as supplier capital. Robust standard errors are reported in parentheses. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

Figure C1: Share of Observations with Missing Firm ID



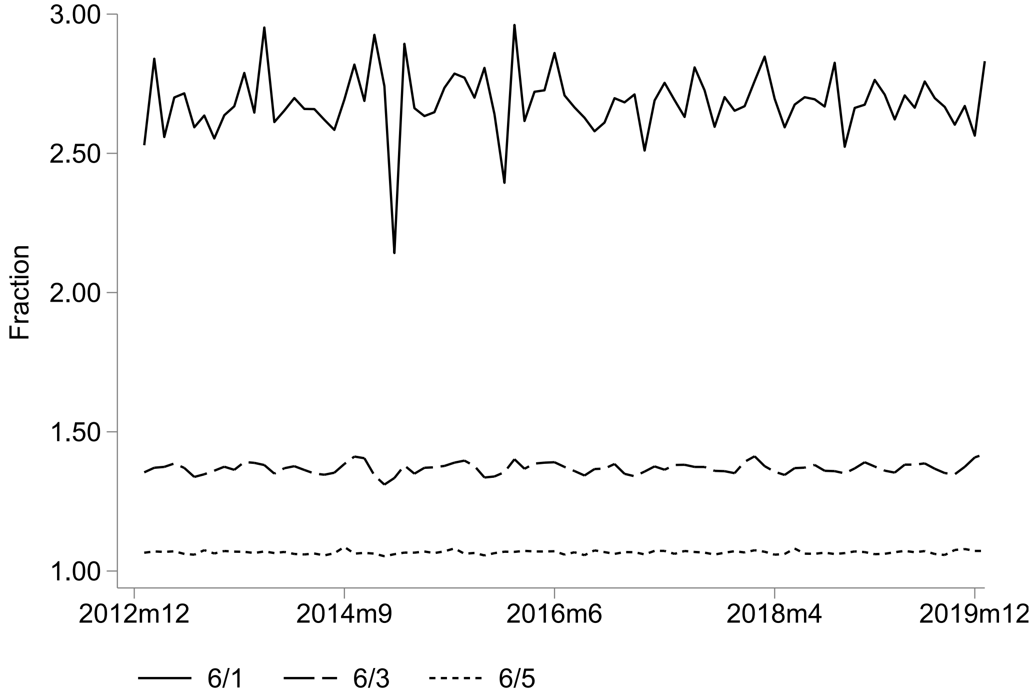
Notes: Figure C1 plots the share of observations (per month) with missing `conpanjivaid`.

Figure C2: Distribution of Firms by Share of Import Value Accounted for by Critical Products



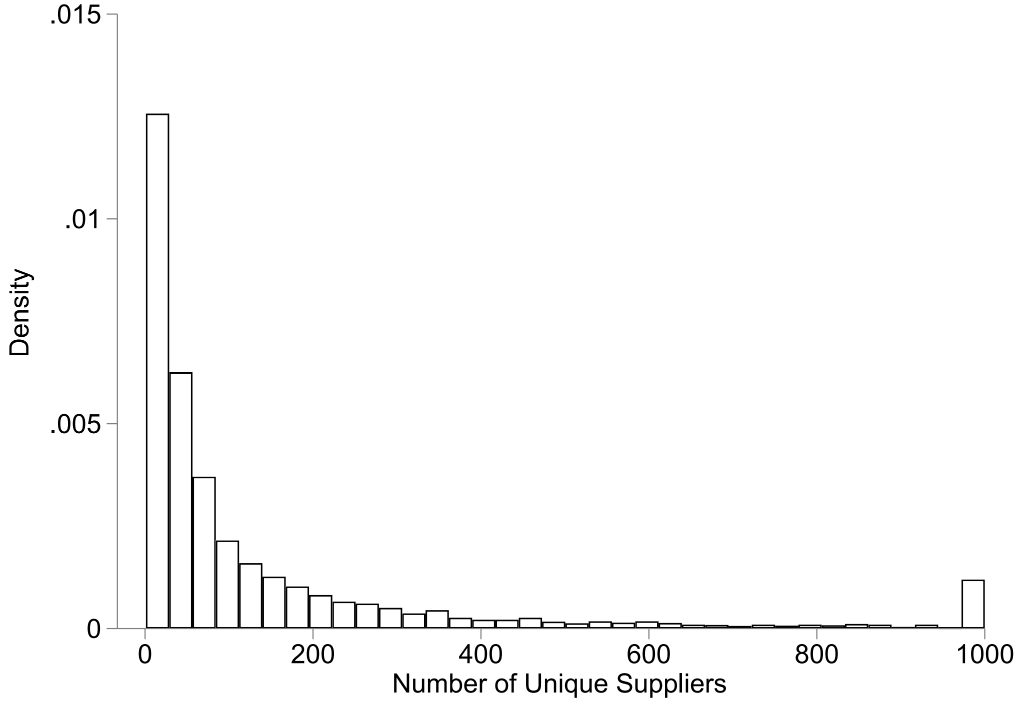
Notes: Figure C2 plots the distribution of public firms with respect to the share of total import value accounted for by critical products.

Figure C3: Illustration of the Imputation Method



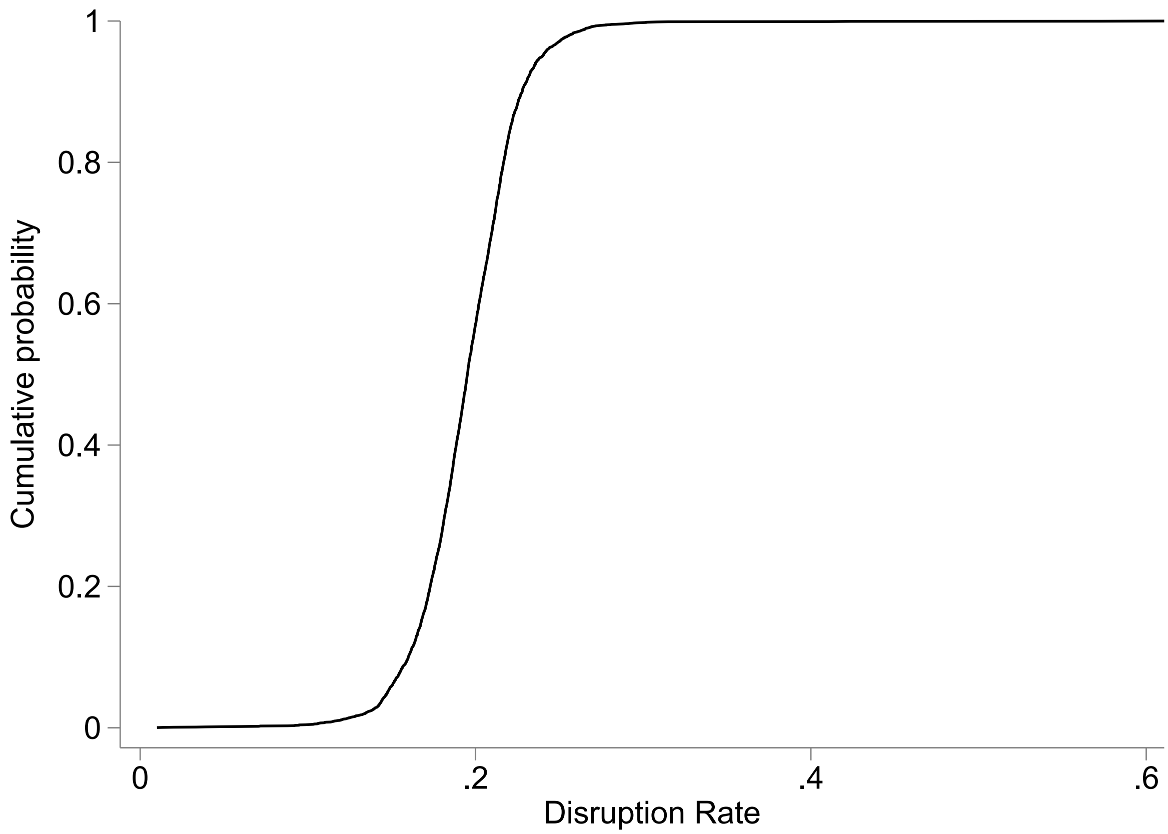
Notes: Figure C3 plots 3 lines. The solid line depicts the ratio of established, temporarily inactive trade pairs ($X = 3, p = 12, v = 6$) that recover over the next 6 months and the number of those which will recover next month (6/1). The dashed and dotted lines correspond to ratios 6/3 and 6/5. Time series have been deseasonalized.

Figure C4: Number of Unique Suppliers: Compustat Sample



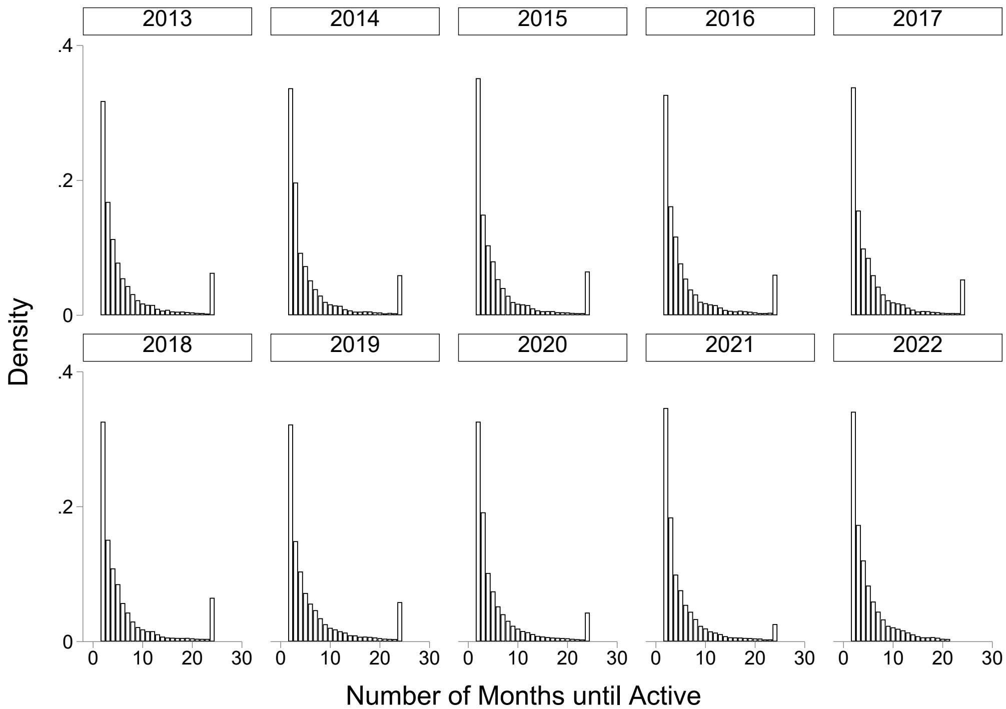
Notes: Figure C4 plots distribution of the number of unique suppliers for U.S. public firms (matched to Compustat data). Right tail is truncated at 1000 unique suppliers.

Figure C5: Distributions of Disruption Rates: Pooled



Notes: Figure C5 plots the cumulative density function of the disruption rate pooled across products and quarters.

Figure C6: Distribution of Inactivity Spells



Notes: Figure C6 plots the distribution of months until next activity (conditional on eventual recovery) by year. Specifically, for each year t we consider all inactive trade pairs in January of year t which were active in December of year $t-1$ and which will eventually trade again in the future. The histogram for year t plots the distribution of number of months until next activity for those trade pairs. The data are winsorized at 24 months.