SUPPLY CHAIN DISRUPTIONS AND SUPPLIER CAPITAL
IN U.S. FIRMS

By

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

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Abstract

We empirically and quantitatively study the impact of supply chain disruptions on U.S. businesses. Leveraging granular shipment-level data on the universe of U.S. seaborne imports with nearly 200 million observations, we construct a measure of disruptions at the individual firm level for the time period 2013-2023. We document a significant heterogeneity in disruption rates among U.S. public firms, with a notable increase observed in recent years. We introduce a notion of supplier capital and investigate the effect of supply disruptions on firms' investment decisions. In the data, firms tend to increase investment in supplier capital following the shock, however, financially distressed firms exhibit a much weaker response. We develop a general equilibrium model with heterogeneous firms and with investment in supplier capital. We show that firms' ability to accumulate supplier capital by making costly investment is an important margin of adjustment in the aftermath of such crises. Financial constraints help account for the heterogeneous treatment effect observed in the data. Two supply chain initiatives proposed by the U.S. government to mitigate disruptions are evaluated. Finally, we document a significant rise in supply disruptions in sectors critical to the U.S. economy and build an index of critical supply disruptions. We show quantitatively that firms relying heavily on imports of critical products experience a much larger decline in output following a disruption shock relative to firms which are not engaged in critical supply chains.

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1 Introduction

Over the last several years, there has been a notable increase in supply chain disruptions, becoming a critical concern for policymakers in the U.S. and worldwide. This has been evidenced by recent initiatives aimed at securing critical supply chains (White House, 2022, 2023c). 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 firm-level measure of supply chain disruptions based on granular data on U.S. seaborne imports. 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 Compustat sample of U.S. listed firms to jointly study supply chain disruptions and various measures of firm performance.

Our firm-level index demonstrates considerable heterogeneity in the levels and persistence of supply disruption across U.S. public firms. Over the last several years there has been not only a substantial increase in supply disruptions in the aggregate but also a pronounced widening of the distribution of supply chain disruptions. Specifically, we find that the interdecile range in the severity of disruptions has doubled since year 2020 as compared with the historical levels. Importantly, while the prevalence of supply chain disruptions has subsided between years 2021-2023, the cross-sectional dispersion has persisted; this indicates the ongoing pressures on supply chains that firms experience.

Consistent with our definition of a supply chain disruption, we measure firm-level supplier capital as the total import volume accounted for by established trade partners. Given the nature of the data we use (seaborne U.S. import), this metric represents international supplier capital. We define investment into supplier capital as a change in supplier capital between subsequent time periods. 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 about 180 twenty-foot equivalent units (TEUs) from established trade partners per quarter, firms in the 90^{th} and 10^{th} percentiles import 1800 and 13 TEUs, respectively. Furthermore, the distribution of supplier capital growth rates is highly dispersed in the cross-section, roughly six times as dispersed as the distribution of physical capital growth rates.

Third, we observe that upon receiving a supply disruption shock, firms tend to increase their investments in supplier capital. However, we note a pronounced heterogeneous treatment effect: financially distressed firms, as measured by leverage, tend to engage in smaller investment in supplier capital following such a shock. Meanwhile, investment in physical capital experiences a decline in response to a supply disruption shock, with this effect being both economically and statistically significant.

Fourth, while larger firms (measured by total assets) exhibit lower investment rates in tangible capital, we do not find a statistically significant difference in average investment rates in supplier capital across the firm-size distribution.

Fifth, when grouping firms by industry, we observe significant variation in average supplier capital across industries. Retail firms, on average, have the largest amount of supplier capital, followed by manufacturing and wholesale industries. Conversely, agriculture, utilities, and transportation firms have the least amount of supplier capital on average. Despite this pronounced variation in supplier capital, industries exhibit similar exposure to supply disruption shocks, as evidenced by the similarity in the average index across industry groups.

From a theoretical perspective, 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 across the state space. 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 consider an environment in which firms unexpectedly encounter a one-period increase in the severity of supply disruptions; subsequently, we trace the economy's transition back to the steady state. With the magnitude of the shock similar to that experienced by firms in recent years, our model predicts that it takes the economy approximately ten quarters to fully recover. Firms' ability to accumulate supplier capital by making costly investment is an important margin of adjustment in the aftermath of such crises; we find that limiting this ability by assuming counterfactually high adjustment costs can substantially delay recovery. Importantly, the model aligns with the data by accounting for the positive investment response into supplier capital and the negative response of investment into physical capital following a supply disruption shock.

By introducing a financial constraint into our economic environment—a non-negativity constraint on dividends—we can qualitatively account for the heterogeneous investment response across constrained and unconstrained firms observed in the data. Specifically, we simulate a panel of firms in the model and find that firms with low dividend levels increase investment into supplier capital by a smaller amount upon receiving a supply disruption shock. Although this financial constraint has a sizable effect on a subset of firms, its aggregate impact is minimal, as evidenced by the nearly identical rate of recovery after the shock across models with and without the constraint.

We use the model to quantify various supply chain initiatives proposed by the U.S. government in response to mounting supply chain challenges (White House, 2022, 2023b). Specifically, we examine two initiatives: leveraging public and private financing to establish new interconnections and providing relief funding to small businesses. In our model, we quantify the first initiative as an investment subsidy for all firms, while the second initiative offers direct subsidies targeting the smallest firms. Our findings reveal that the first initiative increases supplier capital for all firms, also aiding smaller firms in swiftly replenishing their supplier capital stocks after supply disruptions. Similarly, the second initiative incentivizes the smallest firms to accumulate more supplier capital as compared to the baseline. However, we find that the largest firms experience reduced levels of supplier capital as a result of this initiative.

Finally, we assess the impact of a disruption shock on critical suppliers. We first document a significant rise in pressures on supply chains in sectors critical to the overall U.S. economy. The U.S. administration focuses on four key sectors: public health, minerals and materials, energy, and information and communications technology. We find that the minerals and energy sectors have experienced the most pronounced increase in disruptions over the past few years. The granular nature of our data reveals substantial heterogeneity in supply disruptions across subsectors. We classify firms based on the share of their total imports accounted for by critical products and then evaluate the impact of a disruption shock on these two groups. We find that firms heavily reliant on imports of critical products experience a decline in output nearly 80 percent greater than that of firms not engaged in critical supply chains.

Related Literature This paper is related to several strands of the literature.

First, this paper builds an index of supply chain disruptions at the individual firm level. Various other indices have been developed to measure global supply chain disruptions. For example, 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 aggregate disruptions in global supply chains (Benigno, di Giovanni, Groen and Noble, 2022). Bai, Fernández-Villaverde, Li and Zanetti (2024) construct an index of supply disruptions aggregating measures of port congestion around the world.

This paper also contributes to a growing literature studying macroeconomic effects of supply chain disruptions (e.g., Carvalho, Nirei, Saito and Tahbaz-Salehi, 2021; Bonadio, Huo, Levchenko and Pandalai-Nayar, 2021; Elliott, Golub and Leduc, 2022; Alessandria, Khan, Khederlarian, Mix and Ruhl, 2023; Bai, Fernández-Villaverde, Li and Zanetti, 2024). A related strand of literature studies the impact of supply chain disruptions on inflation (e.g. Comin, Johnson and Jones, 2023; Acharya, Crosignani, Eisert and Eufinger, 2023). Our paper is the first to measure supply disruptions at the individual firm level and empirically study the impact of those disruptions on firm-level outcomes.

On a conceptual level, this paper also relates to the literature that considers different types of capital in the production process of firms. This includes intangible capital (McGrattan, 2020; Bhandari and McGrattan, 2021), organizational capital (Atkeson and Kehoe, 2005), customer capital and consumer base (Bils, 1989; Rotemberg and Woodford, 1991; Gourio and Rudanko, 2014; Sedláček and Sterk, 2017). 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, Handfield and Tyler, 2007; Villena, Revilla and Choi, 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 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, discusses the construction details of the supply chain disruptions index, and presents our empirical results. Section 3 develops a firm dynamics model with supplier capital. Section 4 studies the impact of supply disruption shocks and presents other quantitative results. Section 5 discusses critical supply chains. In Section 6, we evaluate two supply chain initiatives proposed by the U.S. government. Finally, Section 7 concludes.

2 Empirical Results

2.1 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 dataset 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.[1]

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

[1] 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.

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), based on container information and other shipment attributes. Table C1 provides the description of key variables contained 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 about 10 percent of US 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

Strategy 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 public firm using fractions of the total firm-level import volume accounted for by individual HS 2-digit product codes as weights.[2]

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

$$\text{Index}_{i,t} = \sum_{j \in \mathcal{N}_i} W_{i,j} \times \text{Index}_{j,t}, \tag{1}$$

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

$$W_{i,j} = \frac{\text{Tot. vol}_{i,j}}{\sum_{j \in \mathcal{N}_i} \text{Tot.vol}_{i,j}}.$$

The import volume is measured in terms of twenty-foot equivalent units (TEU) (variable `volumeteu` in Panjiva dataset).

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

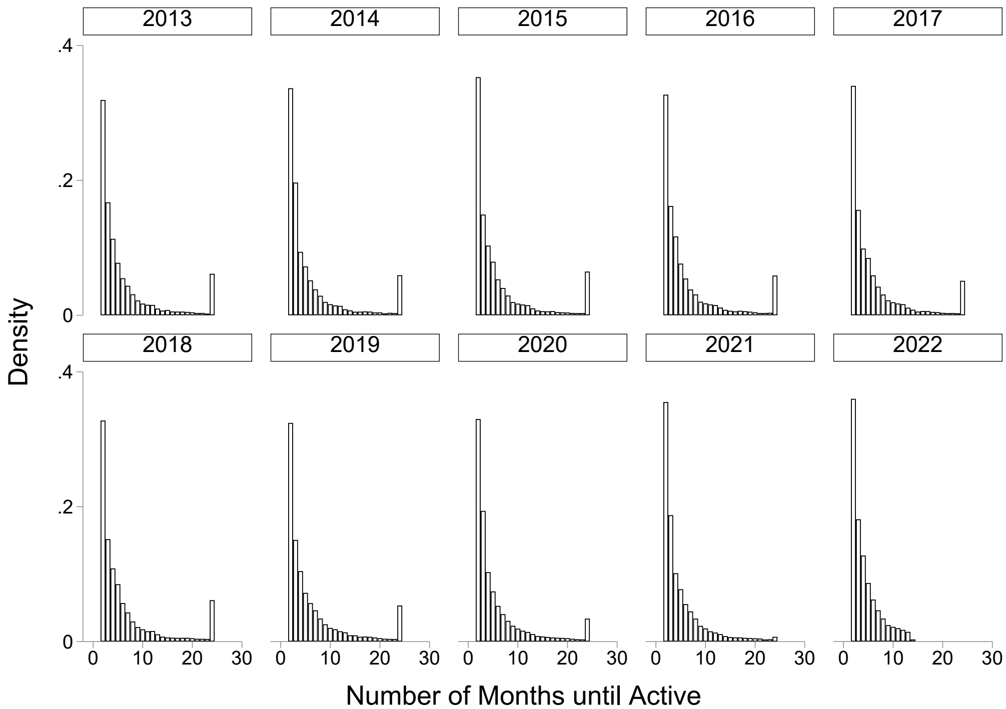
Measuring Supply Chain Disruptions We define our disruptions measure at each time t to capture the fraction of *established* trading partners (defined as the firm-pairs that trade regularly) that *temporarily* cease trading activities:

$$\text{Disruption rate}_{j,t}(X, p, v) = \frac{|\{\text{established}(X, p) \cap \text{inactive} \cap \text{active in future}(v)\}_{j,t}|}{|\{\text{established}(X, p)\}_{j,t}|}. \tag{2}$$

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

[2] Even though it is feasible to construct the index of supply disruptions directly on the firm-by-firm basis, we found that resulting indices are noisy for a number of public firms which have only few trading partners.

Figure 1: Distribution of Inactivity Spells



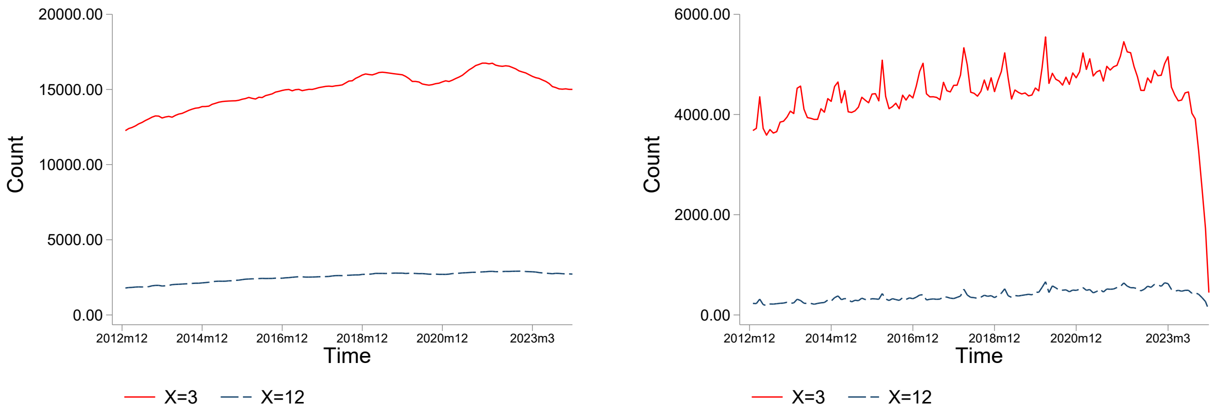
Notes: Figure 1 plots the distribution of months until next activity (conditional on eventual recovery) by year. Specifically, for each year t we consider all inactive trade pairs in January of year t which were active in December of year $t-1$ and which will eventually trade again in the future. The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

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 1). 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 2 plots the time series for the numerator and denominator of Equation (2)

Figure 2: Time-Series Behavior of the Data



(A) Established and recently active

(B) Temp. inactive established

Notes: Figure 2 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 red 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 blue 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 ($v = 6$).

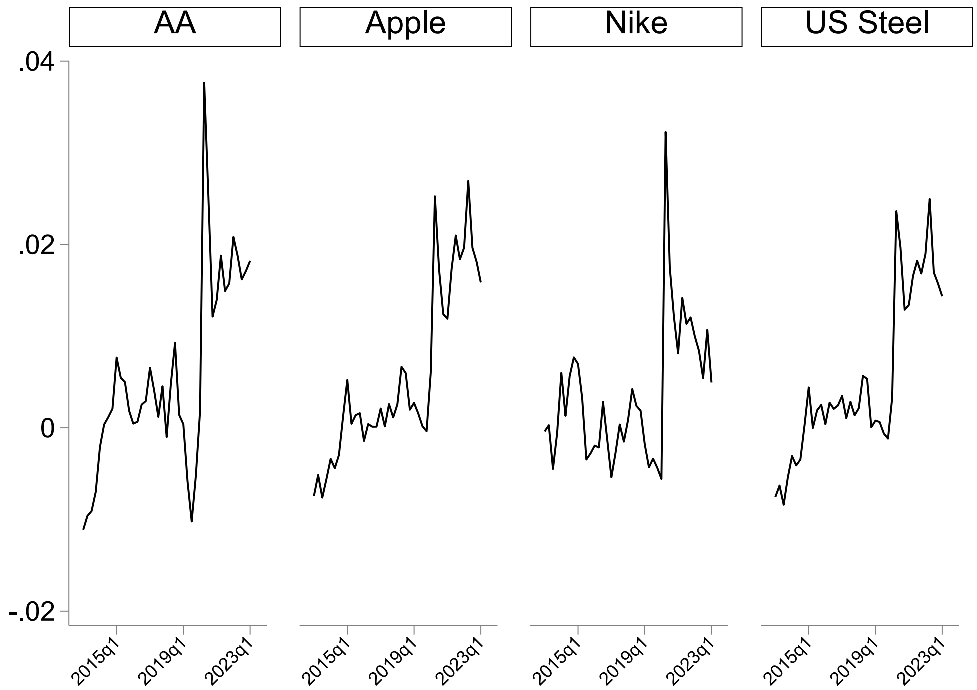
($X = 3$ or 12, $p = 12, v = 6$ for HS code 39 (plastics)). Panel (A) demonstrates that the number of established and recently active trade pairs is smooth; as the requirement for being established becomes more conservative (X rises), the denominator of (2) declines. In turn, Panel (B) shows that the number of temporarily inactive trade pairs is volatile and exhibits seasonality.

The HS 2-digit product category index $\text{Index}_{j,t}$ 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.[3] 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

[3]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, it was 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 3: FIRM-LEVEL DISRUPTIONS: SELECT FIRMS



Notes: Figure 3 plots supply disruption index for select firms. See Section 2.3 for details of the index construction.

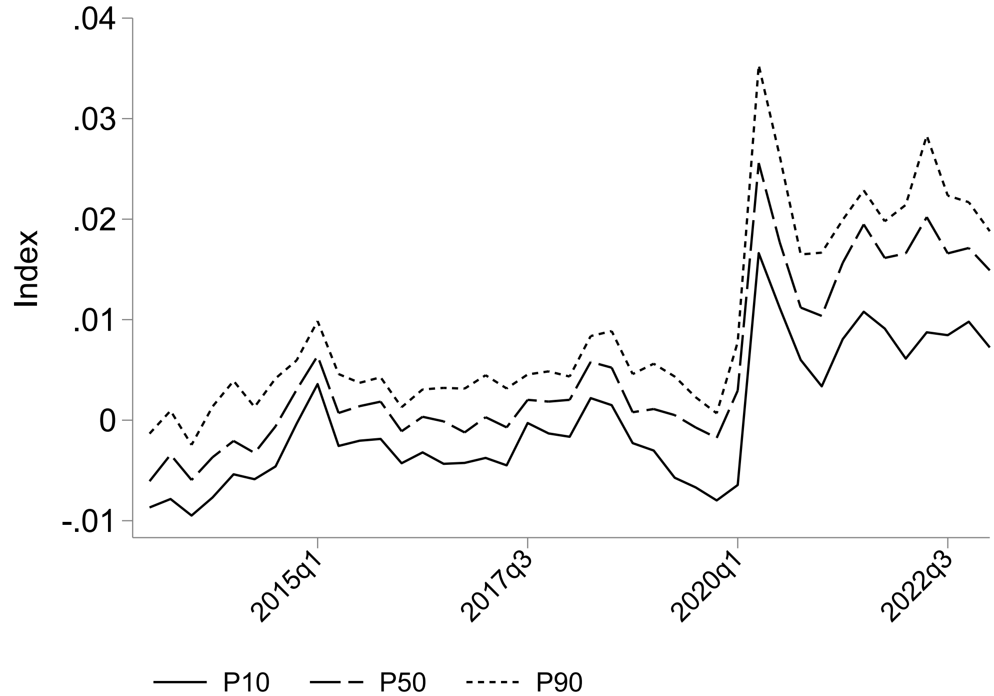
active again. This issue is illustrated by the right panel of Figure 2, where the number of temporarily inactive trade pairs falls to zero as it gets closer to the end of the sample time period.

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

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 3 plots the index of supply disruptions for several select firms in the sample: American Airlines (AA), Apple, Nike and U.S. Steel. The numbers on

Figure 4: Firm-Level Disruptions: Percentiles



Notes: Figure 4 plots various percentiles (by quarter) of the firm-level supply disruptions index. See Section 2.3 for details of the index construction.

the vertical axis show the change in the share of temporarily inactive established trade pairs relative to the historical (pre-2020) average.

The data demonstrate that firms faced supply disruptions of various degrees of magnitude and persistence. Specifically, American Airlines faced a spike in disruptions of about 4 percentage points (pp) above the historical mean at the onset of 2020, while Apple and U.S. Steel show an increase of less than 3pp. At the same time, while disruptions for Nike subsides fairly rapidly, the other three firms faced elevated disruptions at about 2pp above the mean for the next couple of years.

Figure 4 reports the time-series evolution of percentiles of the firm-level index distribution over the sample time period. Several observations stand out. First, the cross-sectional distribution of disruptions was fairly concentrated prior to 2020; the interdecile range was about 1pp. In 2020, the distribution considerably spread out, with interdecile range reaching 2pp. In subsequent years, the average level of disruptions decreased while the overall dispersion persisted; this reflects the on-going pressures on supply chains that some firms still experience.

Table 1 provides summary statistics for select quarters. 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. The size distribution of firms in our sample is right-skewed, with the 90^{th} percentile of any size metric 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 5-fold increase in the average index between 2020Q1 and 2021Q1 (from 0.2pp 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 4.

2.5 Stylized Facts about Supplier Capital and Disruptions

As discussed in Section 2.3, we measure supply chain disruptions as a fraction of established trade pairs that are temporarily inactive. Our metric is thus a measure of international firm-level supplier capital. In what follows, we document and report several empirical facts about supplier capital.

Specifically, we measure a firm's international supplier capital as the total import volume in TEUs 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 volume. 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 volume of the last transaction with that supplier (which, by construction, has occurred over the preceding 24 months) to compute the supplier capital at a given time period. In what follows, we document and report several empirical facts about supplier capital. We structure

Table 1: Summary Statistics: Select Quarters

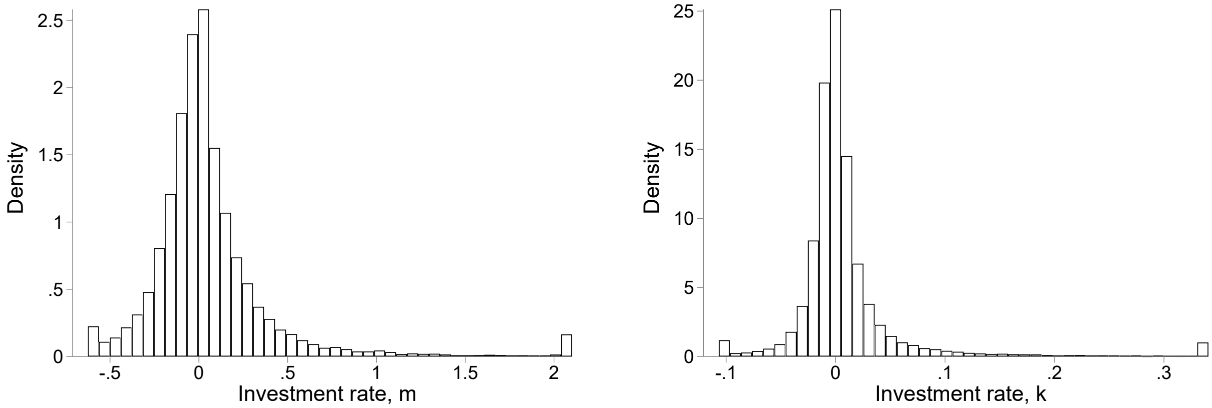
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
2019Q1						
Capital (Log)	809	2.721	2.114	0.133	2.687	5.601
Sup. Capital (Log)	809	5.047	1.927	2.641	5.142	7.458
Employment (Log)	809	2.297	1.742	0.151	2.315	4.491
Sales (Log)	809	2.092	1.785	-0.078	2.026	4.376
Assets (Log)	809	3.748	1.962	1.307	3.697	6.343
Leverage	809	0.330	0.183	0.086	0.325	0.553
Index	809	0.001	0.004	-0.003	0.001	0.005
Sup. Concentration	809	0.604	0.279	0.231	0.590	1.000
Rel. Strength	809	0.489	0.185	0.295	0.448	0.776
2020Q1						
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Capital (Log)	786	2.808	2.064	0.322	2.674	5.642
Sup. Capital (Log)	786	5.053	1.949	2.650	5.179	7.410
Employment (Log)	786	2.349	1.688	0.264	2.379	4.491
Sales (Log)	786	2.068	1.771	-0.041	2.034	4.339
Assets (Log)	786	3.810	1.941	1.436	3.757	6.308
Leverage	786	0.356	0.187	0.118	0.348	0.591
Index	786	0.002	0.005	-0.005	0.003	0.007
Sup. Concentration	786	0.604	0.278	0.228	0.574	1.000
Rel. Strength	786	0.475	0.178	0.291	0.431	0.723
2021Q1						
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
Capital (Log)	766	2.805	2.110	0.312	2.685	5.708
Sup. Capital (Log)	766	5.106	1.969	2.656	5.248	7.529
Employment (Log)	766	2.340	1.746	0.223	2.409	4.492
Sales (Log)	766	2.157	1.806	0.018	2.124	4.453
Assets (Log)	766	3.867	1.983	1.455	3.865	6.456
Leverage	766	0.326	0.176	0.099	0.314	0.545
Index	766	0.011	0.005	0.005	0.011	0.017
Sup. Concentration	766	0.620	0.279	0.245	0.592	1.000
Rel. Strength	766	0.478	0.189	0.288	0.427	0.747

Notes: Table 1 provides summary statistics for select quarters. *Capital* is a measure of physical capital, constructed recursively (Clementi and Palazzo, 2019; Ottonello and Winberry, 2020); *Sup. Capital* is the total import volume 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.

these observations around the following five facts.

Fact 1: Firm-size distribution of supplier capital is highly right-skewed. Summary statistics reported in Table 1 demonstrate that a typical firm imports approximately

Figure 5: Distributions of Capital Growth Rates



(A) Investment rate, m (B) Investment rate, k

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.

181 TEUs from established trade partners, while firms in the 10^{th} and 90^{th} percentiles import 13 and 1800 TEUs, respectively. The firm-size distribution with respect to supplier capital is right-skewed with the coefficient of Kelley skewness of 0.82, which is lower than for physical capital (0.91) but slightly larger than for employment (0.79).

Fact 2: Distribution of supplier capital growth rates is highly dispersed. We next look into distribution of supplier capital growth rates. Panel (A) of Figure 5 shows that the mean of distribution is 0.057, and the distribution is very dispersed (interdecile range is 0.60 and standard deviation is 0.36). For comparison, Panel (B) plots the distribution of physical capital growth rates which exhibits a much smaller dispersion (interdecile range is 0.06 and standard deviation is 0.05). Physical capital also exhibits a high degree of lumpiness (Cooper and Haltiwanger, 2006), as about 40 percent of growth rates are less than 1 percent in absolute value (the corresponding number for supplier capital is 6.8 percent).

Fact 3: Supply chain disruptions are associated with positive investment in supplier capital, although the effect is smaller for financially distressed firms. We measure investment into supplier capital as $\Delta \log m_{i,t+1}$, where $m_{i,t}$ is import volume in TEUs accounted for by established trade partners with whom firm i traded over the preceding (relative to quarter t) two years. 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 $index_{i,t}$ which is the firm-level index of supply disruptions constructed in Section 2.3. We use firm's leverage to proxy for financial conditions; specifically, leverage $l_{i,t}$ is the ratio of firm's debt (both short- and long-term) to total assets.

We estimate different versions of the following model:

$$\Delta \log y_{it+1} = \beta_0 index_{it} + \beta_1 index_{it} \times l_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{3}$$

where $\mathbf{X}_{it-1}$ is a vector of controls that includes at least the intercept, year-quarter and industry fixed effects, as well as lagged logarithms of firm's physical and supplier capital stocks. The dependent variable y is either physical k or supplier capital m. When we evaluate a heterogeneous treatment effect with respect to firm's financial conditions, vector of controls also includes lagged leverage. 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. We standardize leverage over the entire sample to facilitate the interpretation of coefficients. Standard errors are two-way clustered at the firm and industry levels (at NAICS 3-digit level). We winsorize variables at top and bottom 1 percent to reduce the impact of outliers.

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 and statistically significant at 5 percent level. The point estimate suggests that a 1pp increase in the index is associated with about a 1.1pp 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 5 percent level. The estimates indicate that a 1pp increase in the supply disruptions index for firms with 1 standard deviation higher leverage is associated with 0.5pp lower investment rate. This result highlights that the positive average effect reported in Column 1 masks a significantly weaker response from leveraged firms.

Management literature studying supply chains has proposed several firm-level metrics

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

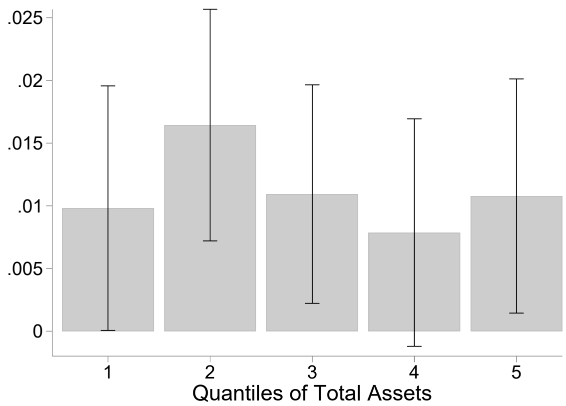
	$\Delta \log m$				
	(1)	(2)	(3)	(4)	(5)
Index	1.1432**	1.1781**	1.1019**	1.1136**	1.0778**
	(0.540)	(0.531)	(0.545)	(0.528)	(0.538)
Index x Leverage		-0.5445**	-0.5080**	-0.5446**	-0.5221**
		(0.252)	(0.254)	(0.255)	(0.256)
Leverage		0.0035	0.0033	0.0035	0.0034
		(0.002)	(0.002)	(0.002)	(0.002)
Rel. Strength			-0.0174***		-0.0107***
			(0.002)		(0.002)
Sup. Concentration				-0.0244***	-0.0201***
				(0.002)	(0.002)
Year-Quarter FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
R^2	0.021	0.021	0.024	0.026	0.027
N	29647	29647	29647	29647	29647

Notes: Table 2 reports OLS estimates of Equation 3. The dependent variable is investment rate into supplier capital $\Delta \log m_{it+1}$. *Index* is a firm-level index of supply chain disruptions constructed in Section 2.3; *Leverage* is a standardized, lagged value of firm's leverage; *Sup. Concentration* is a standardized, lagged measure of supplier concentration; *Rel. Strength* is a standardized, lagged measure of relationship strength. Regressions include year-quarter and industry (at NAICS 3-digit) fixed effects. Standard errors are two-way clustered at the firm and industry levels. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

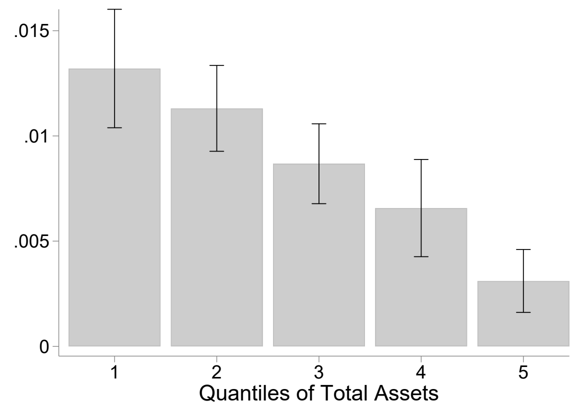
of supply chain management which were found to play an important role in accounting for inventory performance (Jain, Girotra and Netessine, 2013), predicting stock returns (Jain and Wu, 2023), and recovery speed from sourcing interruptions (Jain, Girotra and Netessine, 2021). We use two commonly used metrics—supplier concentration and a measure of relationship strength—to demonstrate that the link between firm investment and our measure of supply disruptions is robust to controlling for these measures of firms' supply chain management strategies. Details on how we construct these measures are relegated to Appendix A.1.

In Columns 3-5, we additionally control for firms' relationship strength and supplier concentration. We observe a notable role played by both of these characteristics; specifically, firms with more concentrated supplier bases and stronger ties with their suppliers tend

Figure 6: Average Investment Rates and Firm Size



(A) Investment rate in supplier capital



(B) Investment rate into physical capital

Notes: Figure 6 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.

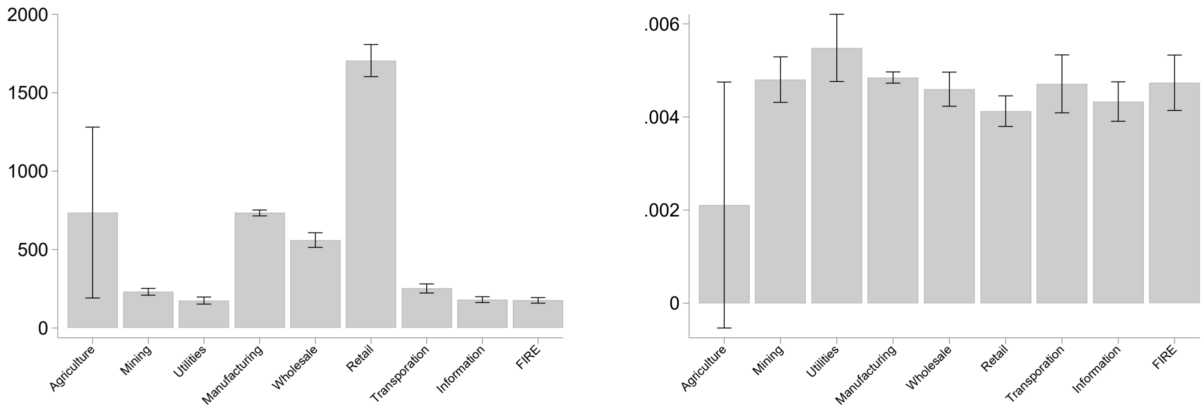
to invest less in supplier capital. However, these controls do not materially impact the magnitude and significance of the interaction between the supply disruptions index and the financial position of the firm.

In Appendix A.2 we also investigate an impact of supply chain disruptions on investment into physical capital and document a large and statistically significant negative effect, although we do not find any sizable heterogeneous treatment effect with respect to the financial position of the firm.

Fact 4: Supplier capital investment rate is similar across the firm-size distribution, while investment rate into physical capital strongly declines in firm size. Do larger firms invest more into 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 6 demonstrates that there is no strong connection between firm size and investment into supplier capital; the 95 percent confidence intervals overlap across all five size groups. If anything, we find moderately higher investment rates for small firms, although the difference is not significant with large firms.

Patterns are very different in the case of investment into physical capital, as evidenced by

Figure 7: Supplier Capital and Supply Disruptions by NAICS 2-Digit Industry



(A) Supplier capital

(B) Supply disruption rate

Notes: Figure 7 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.

Panel (B). The smallest firms tend to exhibit the highest investment rates (with an average of 1.3 percent); the average rate monotonically declines, reaching 0.4 percent for the largest 20 percent of firms.

Fact 5: Supplier capital varies across industries, while exposure to supply disruptions is similar across industries. Panel (A) of Figure 7 shows there is a large variation in supplier capital across industries. Retail firms, on average, have the largest amount of supplier capital, followed by manufacturing and wholesale industries. Agriculture, utilities, and transportation firms are on the other side of the spectrum with the least amount of supplier capital.

Panel (B) shows that despite pronounced variation in supplier capital, industries have similar exposure to supply disruption shocks. The agricultural industry is an exception with a small disruption rate on average; this is due to a very small number of firms in this industry sample (as reflected by the wide confidence interval).

3 Model

In this section, we develop a model based on the empirical findings reported in Section 2. 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 simple financial constraint into the economic environment, we can account for the heterogeneous investment responses across constrained and unconstrained firms, as well as study the aggregate implications of financial frictions.

3.1 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 $\rho_z \in (0,1)$:

$$z_{t+1} = \rho_z z_t + \varepsilon^z_{t+1}, \quad \varepsilon^z_{t+1} \sim \mathcal{N}(0, \sigma_z) \tag{4}$$

Labor Labor market is frictionless with the wage rate W.

Financing There is a representative household which owns all firms; the proceeds from production net of adjustment costs are paid out to the household as dividends. When we study the effect of financial constraints, we assume that firms have to pay non-negative dividends; that is, firms cannot raise funds by issuing equity.

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

3.2 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):

$$v_t(k, m, z) = p^{shock} v_t^{cont}(k, \zeta_t m, z) + (1 - p^{shock}) v_t^{cont}(k, m, z). \tag{5}$$

According to Equation (5), 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 (5) describes the intertemporal choices of the firm:

$$\begin{aligned} v_t^{cont}(k, m, z) = \pi_t(k, m, z) + \max_{k', m' \geq 0} \{ -i_k(k', k) - i_m(m', m) - AC(k', k) - AC(m', m) + \\ + \mathbb{E}_t \left[M_{t+1} v_{t+1}(k', m', z') \right] \}, \end{aligned} \tag{6}$$

where firm's operating profits π are defined as:

$$\pi_t(k, m, z) = \max_{n \geq 0} e^z \left(k^\theta m^\phi n^{1-\theta-\phi}\right)^\kappa - W_t n. \tag{7}$$

$AC(\cdot)$ are capital adjustment costs, and M_{t+1} is the stochastic discount factor.

In Equation (6), $i_x, x \in \{k, m\}$ denote investments into two types of capital:

$$i_k = k' - (1-\delta)k, \tag{8}$$

$$i_m = m' - m. \tag{9}$$

We assume that supplier capital does not depreciate. Alternatively, the supply disruptions shocks can be viewed as stochastic depreciation of supplier capital.

3.3 Household Optimization

The representative household maximizes the discounted stream of utilities subject to the budget constraint. We assume that labor is supplied inelastically, $\overline{N} = 1$. 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:

$$H_t = \max_{c, \xi'} \left[U(c) + \beta \mathbb{E}_t H_{t+1}\right] \tag{10}$$

subject to

$$c + \int \omega_{1,t}(k', m', z') \mathrm{d}\xi_{t+1} \leq W_t + \int \omega_{0,t}(k, m, z) \mathrm{d}\xi_t. \tag{11}$$

The right-hand side of (11) represents the resources available to the household; it consists of firm shares from the previous period, as well as labor income. Part of these resources is consumed, and the rest is reinvested into firm shares.

Utility We assume log-preferences of the household over consumption:

$$U(c_t) = \log(c_t). \tag{12}$$

Let C_t be the household's consumption policy function. 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.

3.4 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. The persistence ρ_z of idiosyncratic productivity process is taken from Ottonello and Winberry (2020). We set the idiosyncratic volatility $\sigma_z = 0.12$.

We set the depreciation rate δ to match average quarterly investment rate in the data (0.008). 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 (0.27 and 0.05, respectively).

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 $\bar{\zeta} = 0.74$.[4] Figure C5 in Appendix reports the distribution of disruption rates in the data.

We obtain production elasticities by estimating the following specification:

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

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.

Columns 1 and 2 of Table C2 in Appendix reports OLS estimates of Equation (13). We find that the exponent on supplier capital is statistically significant at 1 percent level and is

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

approximately 0.07.[5] Moreover, the estimates are robust to controlling for year-quarter and industry fixed effects. In our quantitative implementation, we proportionately re-scale the obtained estimates such that they are consistent with the returns to scale parameter κ.

Table C3 in Appendix summarizes the parameter values.

4 Quantitative Results

In this section, we quantitatively study the impact of a supply disruption shock on the economy. We emphasize the role of adjustment costs on the recovery speed of the aggregate economy in the aftermath of the shock. Additionally, we explore a version of the model with a simple financial friction—non-negativity constraint on dividends—and argue that while the constraint has a muted effect on aggregate dynamics, it has important implications for firms which are constrained upon receiving a supply disruption shock. We also evaluate two supply chain initiatives proposed by the U.S. government, and study the impact of disruption shocks to critical suppliers.

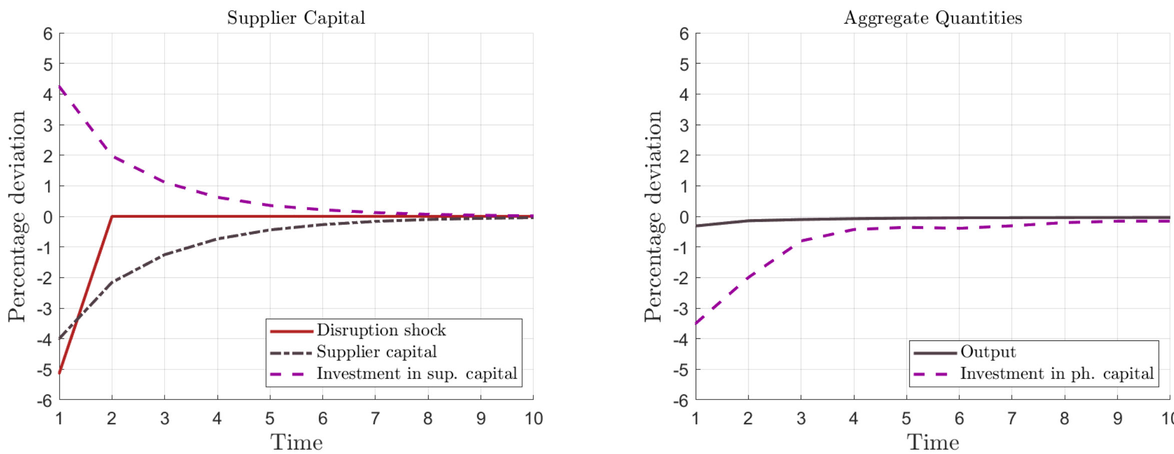
4.1 Impact of Disruption Shock

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 $t = 2, 3, \ldots$ That is, a fraction of supplier capital being destroyed increases by 5 percent for those firms which receive the disruption shock at $t = 1$; this accords well with 3 percentage point increase in the share of established trade pairs being disrupted over the last several years as reported in Figure 4.

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.

[5] 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.

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 4.1. Time $t = 0$ corresponds to the steady-state, and firms learn a sequence of shocks $\{\zeta_t\}_{t=1}^T$ at $t = 1$.

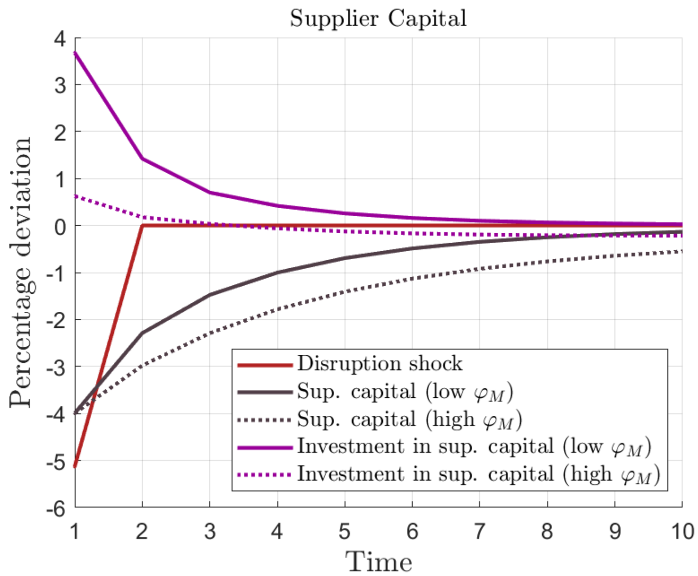
Figure 8 reports the results. Upon impact at $t = 1$, aggregate supplier capital declines by 4 percent relative to the steady-state; at the same time, firms start actively investing into supplier capital as reflected by a 4 percent increase in aggregate investment i_m. It takes the economy about 10 quarters 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 complementarity 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.

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,

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 4.1. 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 fivefold larger value of φ_M.

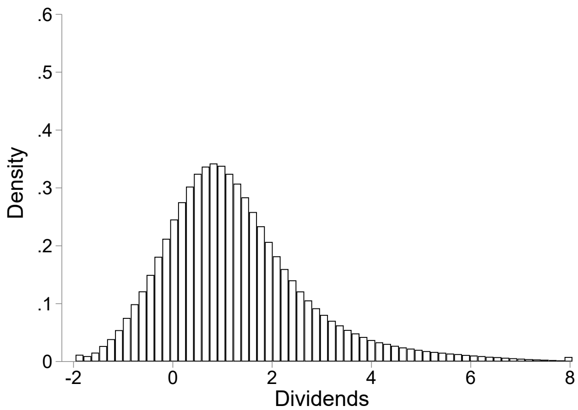
we increase the parameter φ_M from 2.2 to 14 and repeat the transition dynamics exercise described above. Figure 9 compares the dynamics of aggregate supplier capital and investment in supplier capital along the transition path for the two values of φ_M. We find that with higher adjustment costs, investment 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.

4.2 Role of Financial Constraints

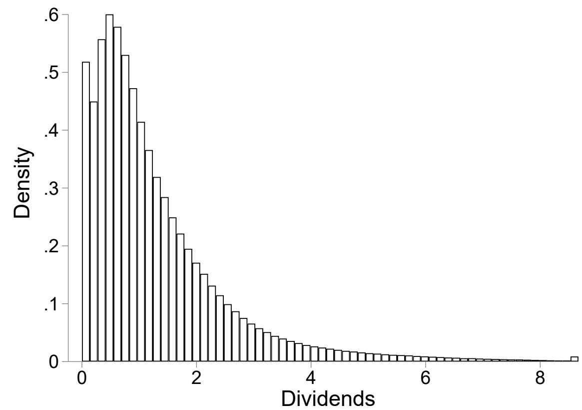
In order to study the impact of financial constraints on firms' investment into supplier capital, we introduce a non-negativity constraint on dividends.[6] Specifically, the firm's problem is

[6] This restriction is routinely introduced in finance, firm dynamics and other strands of the literature to make firms financially constrained (e.g., Whited, 1992; Khan and Thomas, 2013).

FIGURE 10: DISTRIBUTION OF DIVIDENDS AT THE STEADY-STATE



(A) W/o financial constraint



(B) W/ financial constraint

Notes: Figure 10 plots distributions of dividends at the steady-state of the model. Panel (A) corresponds to the model without the non-negativity constraint on dividends. Panel (B) corresponds to the version of the model with the non-negativity constraint on dividends (Equation 14).

still represented by Equations (5)-(8) with an additional constraint:

$$Div_t(k, m, z) := \pi_t(k, m, z) - i_k(k', k) - i_m(m', m) - AC(k', k) - AC(m', m) \geq 0. \quad (14)$$

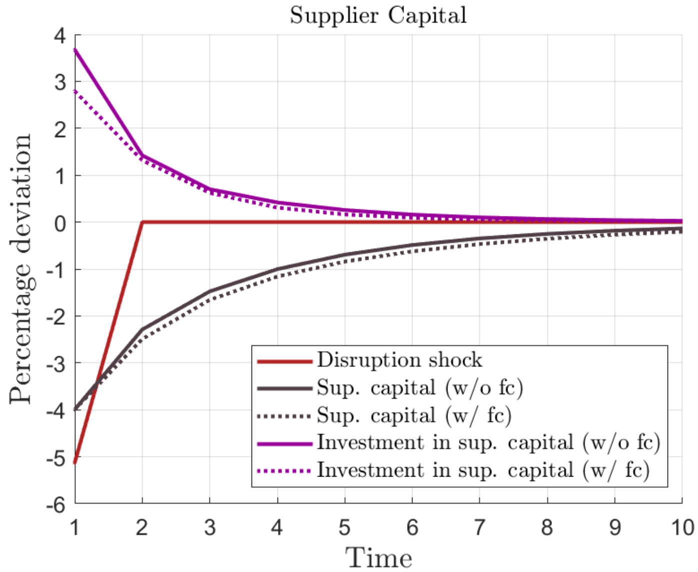
By imposing constraint (14) on the economic environment, we limit the ability of some firms—those with low dividends—to invest into capital stocks. Figure 10 demonstrates the resulting distributions of dividends at steady-states of the two versions of the model. We next study the effect of this constraint on the aggregate dynamics as well as on investment decisions in the cross-section of firms.

4.2.1 Aggregate Effect

How does the financial constraint affect the recovery of the aggregate economy in the aftermath of the supply disruptions shock? To investigate this, we repeat the transition dynamics exercise by imposing a non-negativity constraint on firms' dividends.

Figure 11 demonstrates that the impact of the financial constraint is muted in the aggregate. Investment into supplier capital increases by about one percentage point less in the version of the model with financial frictions; however, the difference is not large enough to

Figure 11: Impact of Supply Disruption Shock: Role of Financial Constraint



Notes: Figure 11 reports results for the perfect foresight transition dynamics exercise as described in Section 4.1. 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.

significantly delay the recovery of the aggregate supplier capital.

4.2.2 Cross-Sectional Implications

Next, we study the impact of supply chain disruptions on firms' investment decisions in the cross-section. We simulate panels of firms from both versions of the model, and study the impact of disruptions on constrained and unconstrained firms. Specifically, we estimate the following specification:

$$\Delta \log y_{it+1} = \beta_0 \text{Share Disrupted}_{it} + \beta_1 \text{Share Disrupted}_{it} \times \mathbf{1}_{\text{Div} \leq 0} + \gamma \mathbf{1}_{\text{Div} \leq 0} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \quad (15)$$

where the coefficient of interest β_1 measures the differential investment response of constrained firms to a supply disruption shock. We label firm i at time t to be constrained if its dividends are non-positive. The vector of controls $\mathbf{X}_{it-1}$ includes an intercept, lagged (logarithms of) physical and supplier capitals, and idiosyncratic productivity. We additionally control for supply disruptions shocks a firm experienced over the preceding four quarters, although the results are similar if we do not include them.

Table 3: Supply Chain Disruptions and Firm Investment: Model-simulated Data

	$\Delta \log m$		$\Delta \log k$	
	(1)	(2)	(3)	(4)
Share Disrupted	0.473	0.531	-0.001	-0.002
Div ≤ 0	0.054	0.077	0.012	0.028
Share Disrupted $\times$Div ≤ 0	-0.227	-0.120	-0.005	-0.003
Year-Quarter FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Model	w/ FC	w/o FC	w/ FC	w/o FC
R^2	0.222	0.258	0.664	0.790

Notes: Table 3 reports OLS estimates of Equation 15. The dependent variable is log change in supplier capital $\Delta \log m_{it+1}$ or physical capital $\Delta \log k_{it+1}$. *Share Disrupted* is a fraction of supplier capital got destroyed; $\mathbf{1}_{\text{Div} \leq 0}$ is a an indicator of non-positive dividends. The vector of controls $\mathbf{X}_{it-1}$ includes an intercept, lagged (logarithms of) physical and supplier capitals, idiosyncratic productivity, as well as supply disruptions shocks a firm experienced over the preceding four quarters. Regressions include year-quarter and firm fixed effects. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

The results are reported in Table 3. The dependent variable in Columns 1 and 2 is investment in supplier capital m. We find that following a supply disruption shock, firms start actively investing into supplier capital; this is consistent with the transition dynamics exercise described in Section 4.1 as well as empirical findings reported in Table 2. However, the effect is weaker for constrained firms; this result mirrors our empirical finding that financially distressed firms tend to invest less into supplier capital after experiencing a disruption.

The second column corresponds to the the model without a non-negativity constraint on dividends. We find that firms with positive dividends respond quantitatively similarly to a disruptions shock across the two versions of the model; this accounts for a similar response of aggregate investment reported in Figure 11. At the same time, the investment response of firms with non-positive dividends is higher relative to the model with the financial constraint. We conclude that financial constraints do have a sizable effect on a subset of firms; however, since those firms account for a small fraction of economic activity, the effect of frictions is not pronounced in the aggregate.

The last two columns show the physical capital investment response. The overall effect is negative, although quantitatively small, and is similar across the two versions of the model.

Firms with non-positive dividends reduce investment stronger as compared to the rest of firms; however, in the model with frictions, the relative investment decline of such firms is stronger.

5 Critical Supply Chains

We now examine supply chain disruptions in U.S. sectors that are identified as critical to the economy.

The White House has issued the Executive Order 14017 "Executive Order on America's Supply Chains" which outlines U.S. policy objectives with respect to strengthening the resilience of the U.S. supply chains.[7] The Order focuses on four critical sectors: Public Health, Critical Minerals and Materials, Energy, and Information and Communications Technology. Consequently, the Department of Commerce's International Trade Administration (ITA) drafted a list of critical goods and materials within four of the supply chains assessed under the Order.[8]

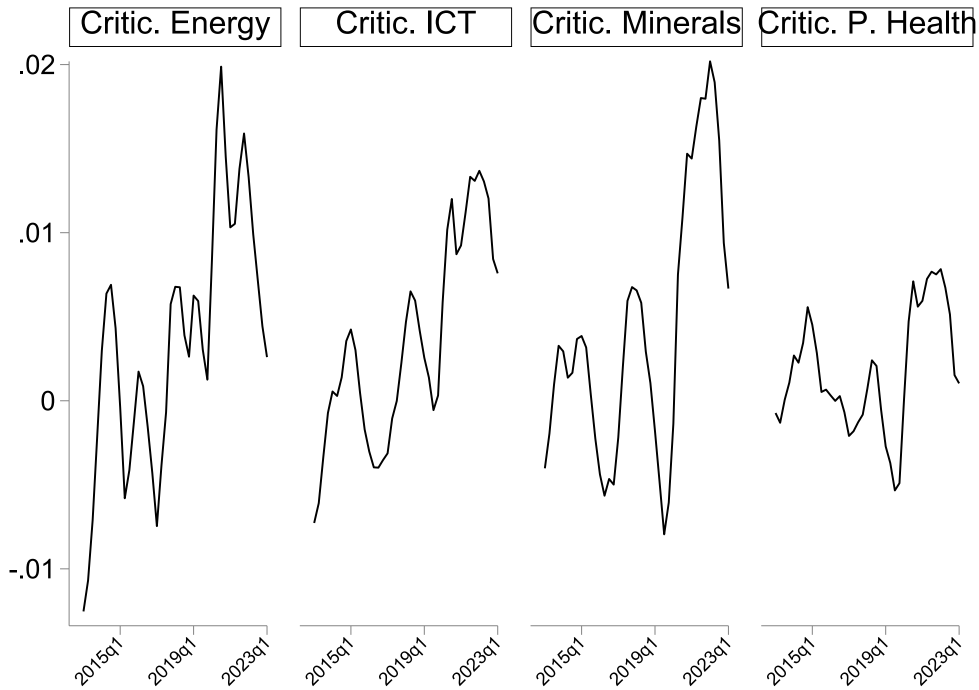
5.1 Index of Critical Supply Chain Disruptions

When it comes to the analysis of critical supply chains, constructing an index based on the fairly crude HS 2-digit classification becomes less meaningful since many subcomponents of the HS 2-digit category are not identified as being critical by the ITA. For example, according to the ITA, 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. For the purpose of analyzing critical supply chains, we thus recompute disruption rates (2) at the HS 4-digit level. We find this level of granularity appropriate since, on one hand, it is much more granular than the HS 2-digit code level we utilized so far, and on the other hand, it allows us to construct measures of disruptions for nearly all HS 4-digit codes. Panjiva data allows us to analyze up to the HS 6-digit level; however, we found that many of those narrowly defined product categories do not have

[7] https://www.whitehouse.gov/p1.

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

Figure 12: Supply Chain Disruptions: Critical Sectors



Notes: Figure 12 plots supply disruption index for critical sectors. Data are smoothed over 3 quarter rolling window. See Section 2.3 for details of the index construction.

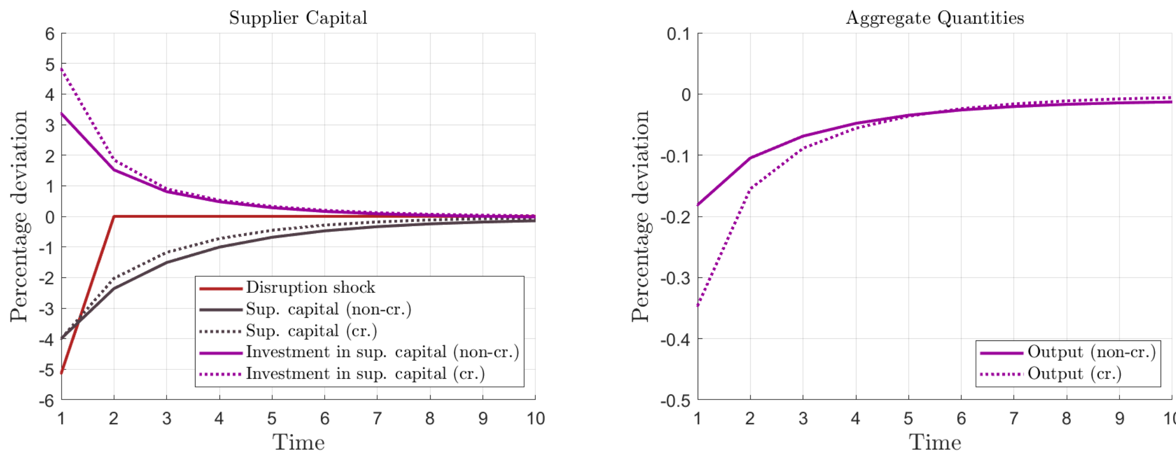
enough observations to compute a disruption rate. For example, there are only 38 unique trade pairs for HS 8541.50 (semiconductor devices, except photosensitive and photovoltaic cells) and 47 unique trade pairs for HS 8533.10 (fixed carbon resistors). Only a subset of those trade pairs satisfies the criteria for being considered established, and as a result, this level of granularity becomes impractical for our purposes. Moreover, we chose to reduce the set of tuning parameters since, in some cases (corresponding to $X = 9$ and $X = 12$), certain product categories do not have any established trade pairs.

Once we derive a measure of disruption rate for each HS 4-digit product category, we construct an index of disruptions for each critical sector by taking an average of the product-specific indices of supply disruptions, using Census data on total containerized import value by HS category as weights.[9]

Starting from critical supply chains as identified by the ITA, Figure 12 reports supply

[9] https://www.census.gov/p1.

FIGURE 13: IMPACT OF SUPPLY DISRUPTION SHOCK: CRITICAL VS. NON-CRITICAL SUPPLIERS



(A) Supplier capital (B) Output

Notes: Figure 13 reports results for the perfect foresight transition dynamics exercise as described in Section 4.1. *Critical* refers to firms for which critical products account for over 80 percent of their imports; *Non-critical* refers to firms for which critical products account for less than 20 percent of their import volume. Time $t = 0$ corresponds to the steady-state, and firms learn a sequence of shocks $\{\zeta_t\}_{t=1}^T$ at $t = 1$.

disruption indices for the four critical sectors. We find that the energy and critical minerals and materials sectors experienced the largest increases in supply disruptions over the last several years. Specifically, these sectors saw up to a two percentage point increase in the share of temporarily disrupted trade pairs among established trade pairs relative to the historical average.

Exploiting the granular nature of the data, we can also examine disruptions at the sub-sector level (see Figures C6–C9 in the Appendix). For example, we find that diagnostics equipment, audiovisual equipment and solar energy are the subsectors of the critical public health, ICT and critical energy sectors, respectively, that saw the highest disruption rates.

5.2 Impact of Disruption Shock to Critical Suppliers

We now examine the quantitative impact of a disruption shock that affects critical suppliers. In our model, supplier capital encompasses both critical and non-critical suppliers. The data reveal a bimodal distribution of public firms with respect to the share of imports accounted for by critical products (as identified by the ITA). Specifically, there is a substantial number of firms with a low share of such products and, concurrently, a significant number of firms for which critical products make up almost all their imports (see Figure C2 in the Appendix).

We repeat the transition dynamics exercise for two versions of the model. The first version, which we refer to as critical, is comprised of firms with over 80 percent of their imports being critical. Correspondingly, the version of the model for firms with less than 20 percent of their total import volume accounted for by critical products is referred to as non-critical. We re-estimate the production technology for these two groups of firms and find that the exponent for supplier capital is 0.094 for the first group, and 0.056 for the second group (see Columns 3 and 4 in Table C2).

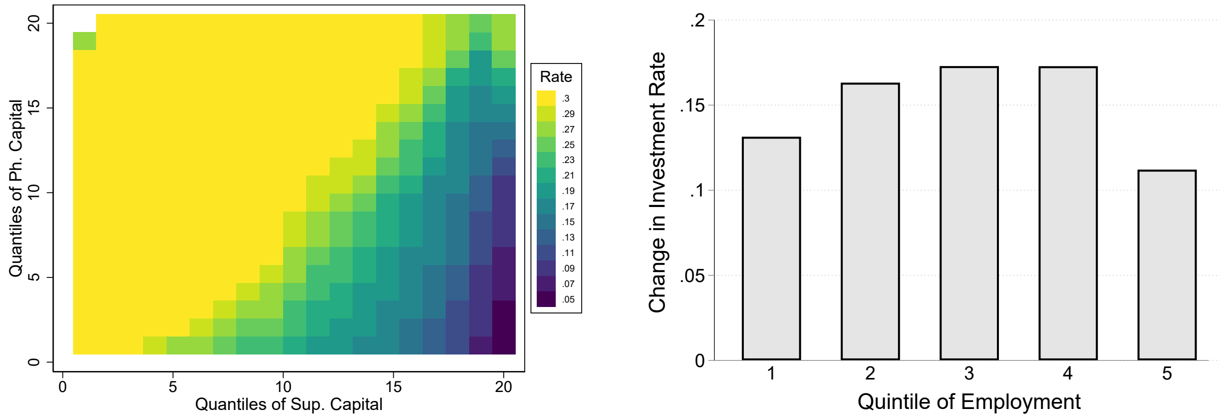
Panel (A) of Figure 13 demonstrates that the investment into supplier capital for critical firms rises by nearly 40 percent more relative to non-critical firms upon impact. This is intuitive given that supplier capital accounts for a share of output twice as large compared to non-critical firms, and such firms have stronger incentives to replenish their supplier capital as soon as possible. As a result, critical firms replenish their supplier capital stock about one quarter faster relative to non-critical firms.

Panel (B) demonstrates that the aggregate output of critical firms declines by 0.35 percentage points upon impact, which is nearly 80 percent more relative to non-critical firms. Provided that critical firms replenish their supplier capital stocks more rapidly, it takes both groups of firms similar amount of time to close the output gap.

6 Evaluation of Supply Chain Initiatives

In response to unprecedented pressures on supply chains that U.S. businesses experienced over the last several years, the U.S. government has proposed several initiatives to strengthen supply chains critical to America's economic and national security (White House, 2023a). These initiatives are designed to enhance the resilience of supply chains, ensuring timely delivery of products to consumers and reliable supplies for businesses. In this section, we evaluate two proposed initiatives through the lens of our model.

Figure 14: Investment in Supplier Capital in Cross-Section



(A) Investment rate change (B) Investment rate gap

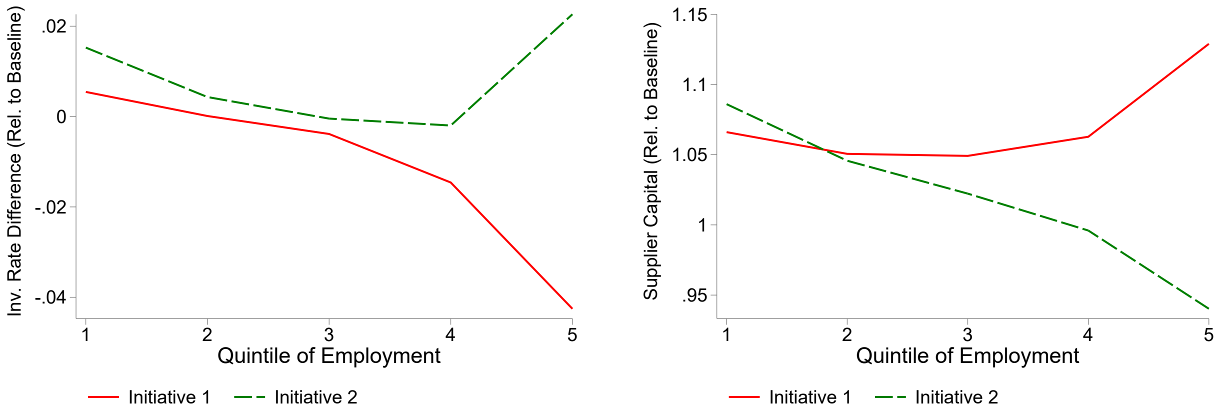
Notes: Figure 14 consists of two panels. Panel (A) plots the average investment rate into supplier capital $\frac{m'(k,m,z)-m}{m}$ in (k,m)-space at the steady-state of the model. Panel (B) plots the difference in the average investment rate in supplier capital between firms that experience a disruption shock and those which do not by employment quintile.

Initiative 1: Leverage public and private financing to create novel interconnections and secure critical supply chains. In order to enhance global supply chains through innovative multilateral partnerships, the United States is leading efforts via the Partnership for Global Infrastructure and Investment. This initiative aims to mobilize public and private financing to encourage investments and develop transformative economic corridors. These efforts seek to diversify global supply chains and create new opportunities for U.S. businesses.

In the context of our model, we interpret this initiative as an investment subsidy $x \in (0,1)$, whereby for each unit of (positive) investment into supplier capital i_m a firm pays $(1-x)i_m$. We assume that this subsidy is financed by a lump-sum tax levied on the consumer; the size of the tax is $T_t = \int x i_m(k,m,z)\mathbf{1}_{i_m(k,m,z)>0} \mathrm{d}\mu_t$ where μ_t is the distribution of firms across the state-space at time t.

Initiative 2: Alleviate specific supply chain disruptions by providing relief funding to small businesses. The U.S. administration worked with Congress to enact new legislation aimed at addressing specific supply chain disruptions and enhancing future resilience. These efforts build on previous initiatives to foster competition, including relief

FIGURE 15: EVALUATION OF SUPPLY CHAIN INITIATIVES



(A) Investment rate gap

(B) Average supplier capital

Notes: Figure 15 consists of two panels. Panel (A) plots the change in the average investment rate in supplier capital between firms that experience a disruption shock and those which do not by employment quintile. Reported numbers on the vertical axis are differences with the baseline model. Panel (B) plots the average supplier capital relative to the baseline model by employment quintile.

funding provided to over 6 million small businesses in recent years (White House, 2023b). In the model, we study the effects of this initiative by providing subsidies to small firms. Specifically, we provide subsidies as a fixed proportion of profits to firms that have below median employment.

Results We evaluate these initiatives by studying their impact on investment rate in supplier capital, as well as the level of supplier capital. Specifically, we choose the subsidy rate of 20 percent for both initiatives.

Panel (A) of Figure 14 illustrates significant variation in investment rates across firms in the cross-section. Rates range from less than 5 percent for firms with high supplier capital and low physical capital to over 30 percent for those with low levels of supplier capital. Investment rates notably increase following a supply disruption shock as firms try to restore their supplier capital stocks. Panel (B) reveals that, in the model, firms experiencing a disruption exhibit investment rates approximately 15 percentage points higher as compared to those unaffected by disruptions. This gap varies non-monotonically with firm size, as measured by employment. Smaller firms typically have low or even negative dividends, as evidenced in Figure 10, and possess fewer resources to make significant investments following a disruption shock. Conversely, larger firms often possess excess capital, and disruption shocks frequently help them align their capital stocks with desired levels, avoiding the need to pay adjustment costs.

We find that the investment subsidy aimed at building new interconnections (Initiative 1) indeed achieves the goal as firms accumulate on average more supplier capital as depicted in Panel (B) of Figure 15. Across the firm-size distribution, firms carry from 6 to about 15 percent more capital relative to the baseline. We also find that this subsidy slightly increases the gap in investment rates for the smallest firms (Panel (A)) which we interpret as a relative ease with which those firms can restore supplier capital stocks after experiencing a disruption. On the other hand, the gap becomes lower for the largest firms since those firms tend to accumulate much more supplier capital relative to the baseline.

Turning to Initiative 2, we find that, in a response to subsidies to the smallest 50 percent of firms, those firms indeed accumulate more capital relative to the baseline. A 20 percent subsidy we considered increases supplier capital by up to 9 percent among the smallest 20 percent of firms. At the same time, we find that this policy has an adverse impact on the largest firms as they end up having about 5 percent lower supplier capital. The investment rate gap between disrupted and non-disrupted firms increases across all size quintiles, with the most pronounced effect in the first and fifth bins. Initiative 2 achieves a goal in a sense that the smallest firms are now able to respond more swiftly to supply disruptions and restore supplier capital faster. It, however, comes at a cost of lower supplier capital among the largest enterprises.

7 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. Our model predicts a ten-quarter recovery period after a supply disruption shock similar in magnitude to what firms experienced in recent years. Financial frictions help the model account for the data. We show that firms relying heavily on imports of critical products experience a much larger decline in output following a disruption shock relative to firms which are not engaged in critical supply chains. Finally, we evaluate two U.S. government supply chain initiatives and find that they incentivize the accumulation of supplier capital with differing impacts across the firm-size distribution.

References

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.

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

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

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.

Clementi, Gian Luca and Dino Palazzo, "Investment and the Cross-Section of Equity Returns," *Journal of Finance*, 2019, *74*, 281–321.

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.

Elliott, Matthew, Benjamin Golub, 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.

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

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.

Khan, Aubhik and Julia Thomas, "Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity," *Journal of Political Economy*, 2013, *121*, 1055–1107.

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.

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

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.

_ , "Fact Sheet: President Biden Announces New Actions to Strengthen America's Supply Chains, Lower Costs for Families, and Secure Key Sectors," 2023.

— , “Fact Sheet: White House Competition Council Announces New Actions to Lower Costs and Marks Second Anniversary of President Biden’s Executive Order on Competition,” 2023.

— , “Issue Brief: Supply Chain Resilience,” 2023.

Whited, Toni, “Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data,” *Journal of Finance*, 1992, *47*, 1425–1460.

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.

Appendix

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

by Ernest 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 volume of imports (in TEUs) by firm i from supplier j in category c, and IV_{itc} is the total volume 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:

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

Table A1: Supply Chain Disruptions and Firm Investment in Physical Capital

	$\Delta \log k$				
	(1)	(2)	(3)	(4)	(5)
Index	-0.1948**	-0.2064**	-0.2044**	-0.2057**	-0.2043**
	(0.097)	(0.096)	(0.095)	(0.095)	(0.095)
Index x Leverage		-0.0347	-0.0356	-0.0347	-0.0356
		(0.047)	(0.047)	(0.047)	(0.047)
Leverage		-0.0025***	-0.0025***	-0.0025***	-0.0025***
		(0.001)	(0.001)	(0.001)	(0.001)
Rel. Strength			0.0004		0.0004
			(0.001)		(0.000)
Sup. Concentration				0.0003	0.0001
				(0.001)	(0.000)
Year-Quarter FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
R^2	0.128	0.130	0.130	0.130	0.130
N	29647	29647	29647	29647	29647

Notes: Table A1 reports OLS estimates of Equation 3. The dependent variable is investment rate into physical capital $\Delta \log k_{it+1}$. *Index* is a firm-level index of supply chain disruptions constructed in Section 2.3; *Leverage* is a standardized, lagged value of firm's leverage; *Sup. Concentration* is a standardized, lagged measure of supplier concentration; *Rel. Strength* is a standardized, lagged measure of relationship strength. Regressions include year-quarter and industry (at NAICS 3-digit) fixed effects. Standard errors are two-way clustered at the firm and industry levels. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

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 volume 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 Supply Disruptions and Investment into Physical Capital

Table A1 presents results for investment in physical capital. The coefficient on the supply disruptions index is negative and statistically significant at 5 percent level. The point estimate suggests that a 1pp increase in the index is associated with 0.2pp decline in the physical capital investment rate. The interaction with firm leverage is negative, but this time it is statistically insignificant and quantitatively small. Additionally, we do not find any material role for supply chain management strategies in explaining firm investment in physical capital; the coefficients for relationship strength and supplier concentration are small and statistically insignificant.

Appendix B: Model Appendix

B.1 Definition of Equilibrium

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

$$\Big\{v, v^{cont}, n, k', m', W, H, C, \Xi, \mu\Big\},$$

such that:

1. H solves the household's problem (10)-(11) and $\{C, \Xi\}$ are the corresponding policy functions,

2. $\{v, v^{cont}\}$ solve the firm's problem (5)-(14), 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. goods market clears:

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

   where

$$\begin{aligned}
I_K &= \int i_k(k, m, z)\mathrm{d}\mu \\
I_M &= \int i_m(k, m, z)\mathrm{d}\mu \\
AC_K &= \int \frac{\varphi_K}{2}\left(\frac{k'(k, m, z) - k}{k}\right)^2 k\mathrm{d}\mu \\
AC_M &= \int \frac{\varphi_M}{2}\left(\frac{m'(k, m, z) - m}{m}\right)^2 m\mathrm{d}\mu;
\end{aligned}$$

5. 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 4);

6. 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 $\boldsymbol{\Theta} = \{\theta^{a,b,c}\}$ 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.[10] 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

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

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: firms learn that there will be a disruption shock at $t = 2$;

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

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 $t = T - 1$:

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

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:

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

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

	Pooled		By subgroup	
	(1)	(2)	(3)	(4)
Capital (Log)	0.3493***	0.3499***	0.3588***	0.3953***
	(0.003)	(0.005)	(0.011)	(0.008)
S. capital (Log)	0.0618***	0.0664***	0.0555***	0.0938***
	(0.002)	(0.003)	(0.004)	(0.005)
Employment (Log)	0.5546***	0.5690***	0.5591***	0.4930***
	(0.004)	(0.005)	(0.012)	(0.008)
Year-Quarter FE	—	✓	✓	✓
Industry FE	—	✓	✓	✓
Sample	—	—	Cr. share ≤ 0.2	Cr. share ≥ 0.8
R^2	0.863	0.911	0.899	0.934
N	30946	30946	10282	7563

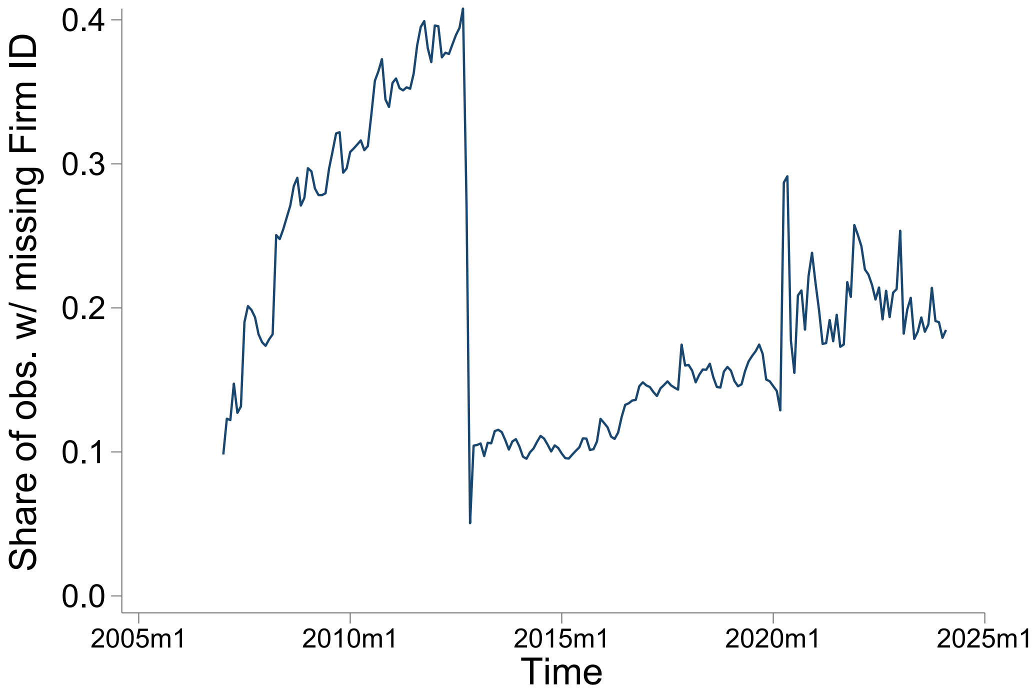
Notes: Table C2 reports OLS estimates of the following specification: $\log y_{it} = \beta_0 \log k_{it} + \beta_1 \log m_{it} + \beta_2 \log n_{it} + \lambda \mathbf{X}_{it} + \varepsilon_{it}$, where y_{it} is sales, m_{it} is supplier capital, k_{it} is physical capital, and n_{it} denotes employment.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

Table C3: Parameter Values

Parameter	Description	Value	Target/Source	Data	Model
β	Discount factor	0.99			
θ	Physical capital share	0.37	See text		
ϕ	Supplier capital share	0.05	See text		
κ	Returns to scale	0.85			
ρ_z	Persistence of idiosyncratic AR(1)	0.90			
σ_z	Std of idiosyncratic AR(1)	0.12			
φ_K	Quadratic adj. cost (k)	0.70	$\sigma[\frac{i_k}{k}]$	0.05	0.04
φ_M	Quadratic adj. cost (m)	0.95	$\sigma[\frac{i_m}{m}]$	0.25	0.17
δ	Depreciation (k)	0.008	$\mathbb{E}[\frac{i_k}{k}]$	0.008	0.008
p^{shock}	Probability of disruption shock	0.83	See text		
$\bar{\zeta}$	Average share of surviving s. capital	0.74	See text		

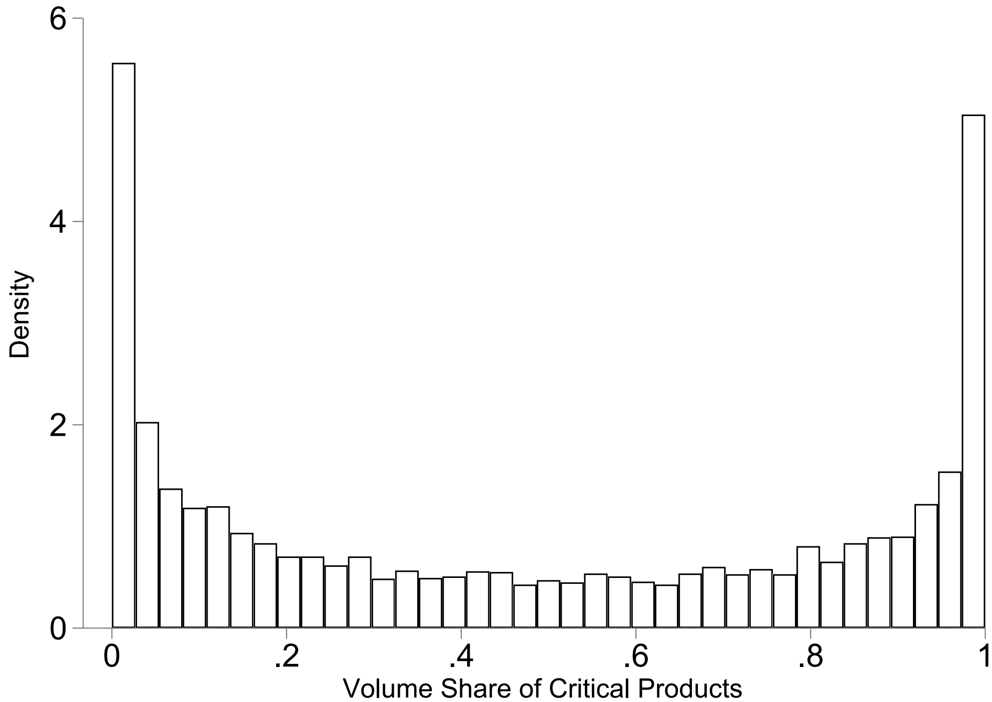
Notes: Table C3 reports parameter values.

Figure C1: Share of Observations with Missing Firm ID



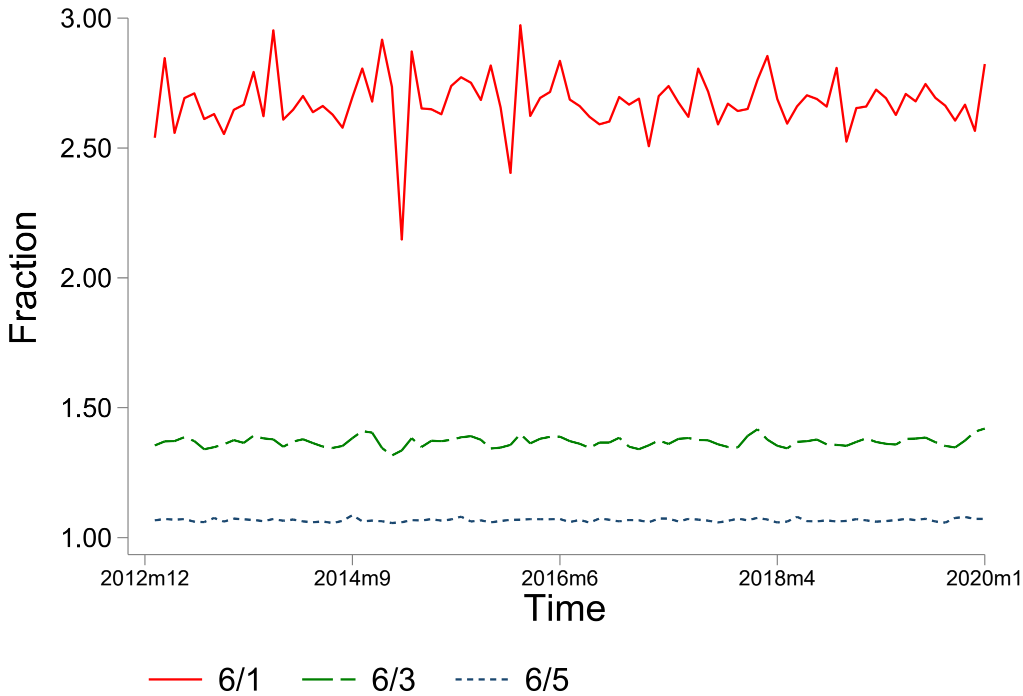
Notes: Figure C1 plots the share of observations (per month) with missing `conpanjivaid`.

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



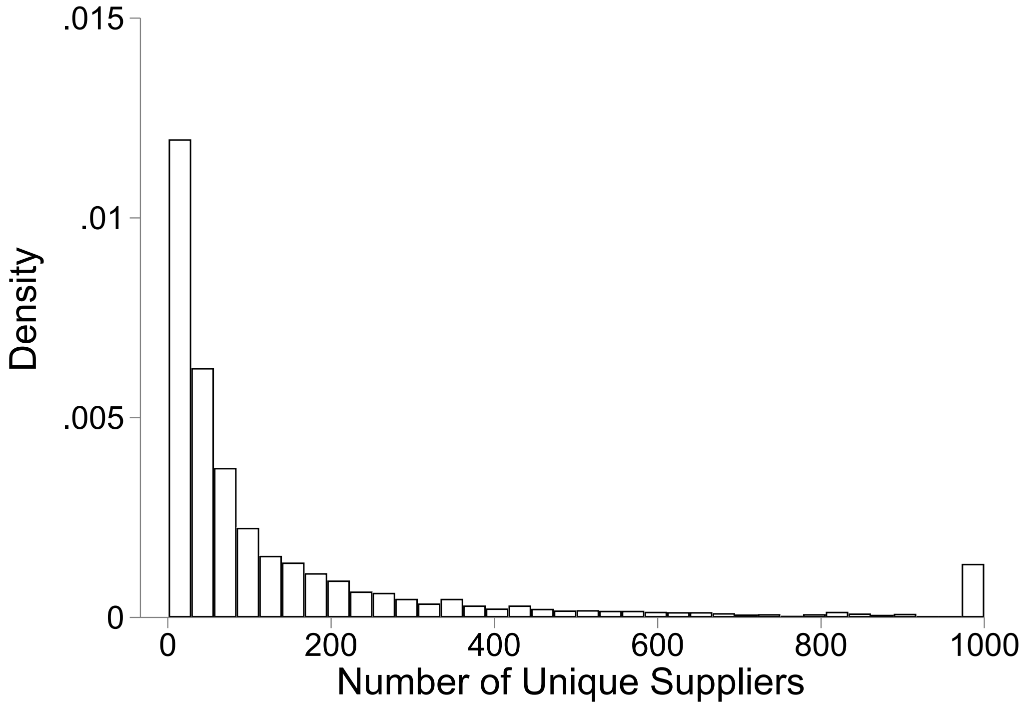
Notes: Figure C2 plots the distribution of public firms with respect to the share of total import volume accounted for by critical products.

Figure C3: Illustration of the Imputation Method



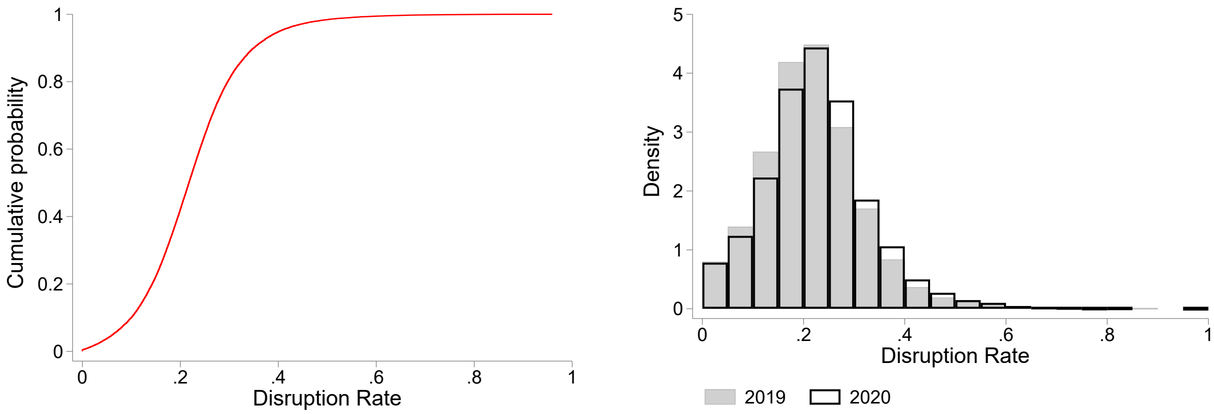
Notes: Figure C3 plots 3 lines. The solid red line depicts the ratio of established, temporarily inactive trade pairs ($X = 3, p = 12, v = 6$) that recover over the next 6 months and the number of those which will recover next month (6/1). The green dashed and blue dotted lines correspond to ratios 6/3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

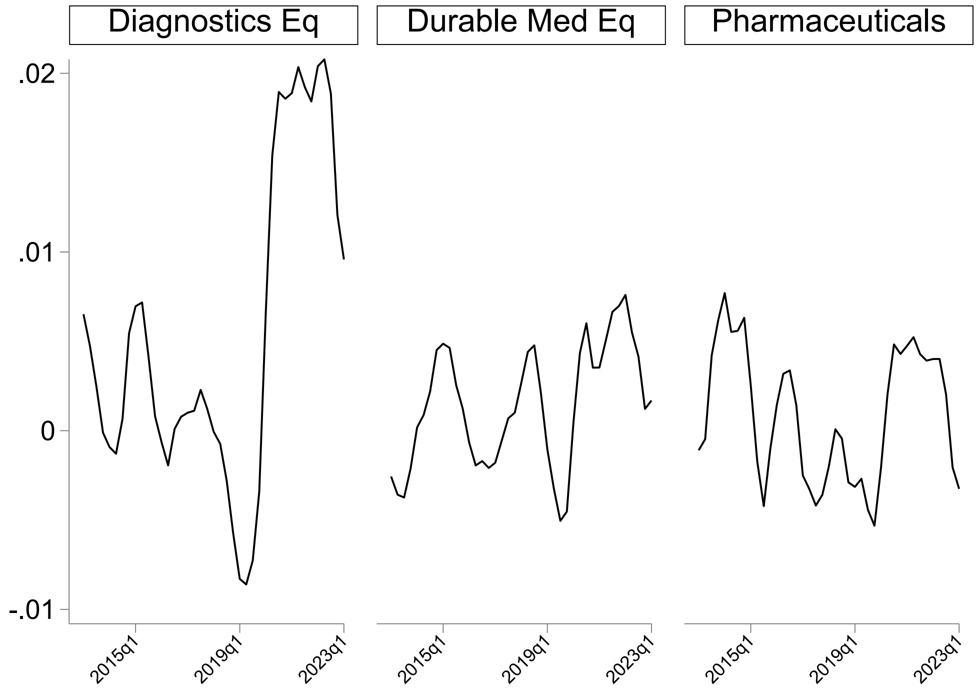


(A) Investment rate, k

(B) Investment rate, m

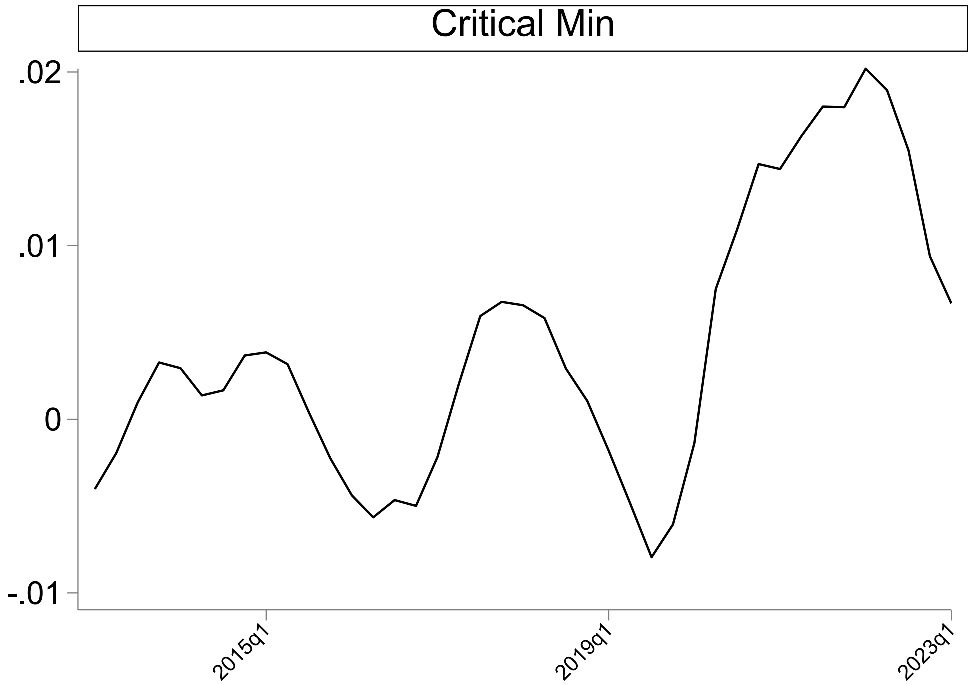
Notes: Figure C5 consists of 2 panels. Panel (A) plots the cumulative density function of the disruption rate. Panel (B) plots histograms of the disruption rate for years 2019 (grey bars) and 2020 (hollow bars).

Figure C6: Supply Disruptions Index: Public Health



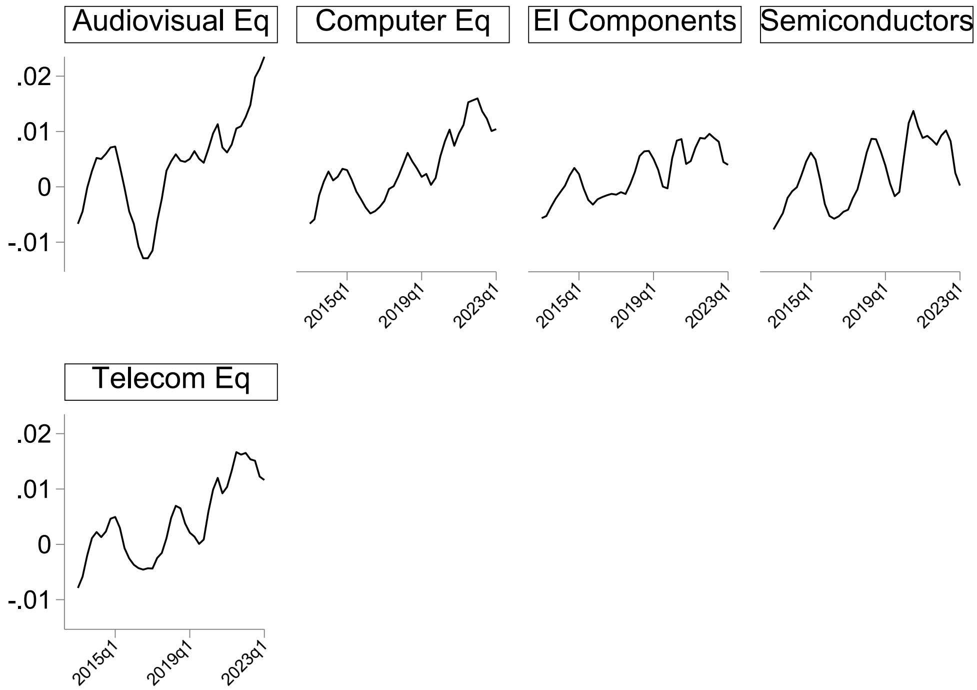
Notes: Figure C6 plots supply disruptions index for Public Health subsectors. For details on index construction, see Section 2.3.

Figure C7: Supply Disruptions Index: Critical Minerals and Materials



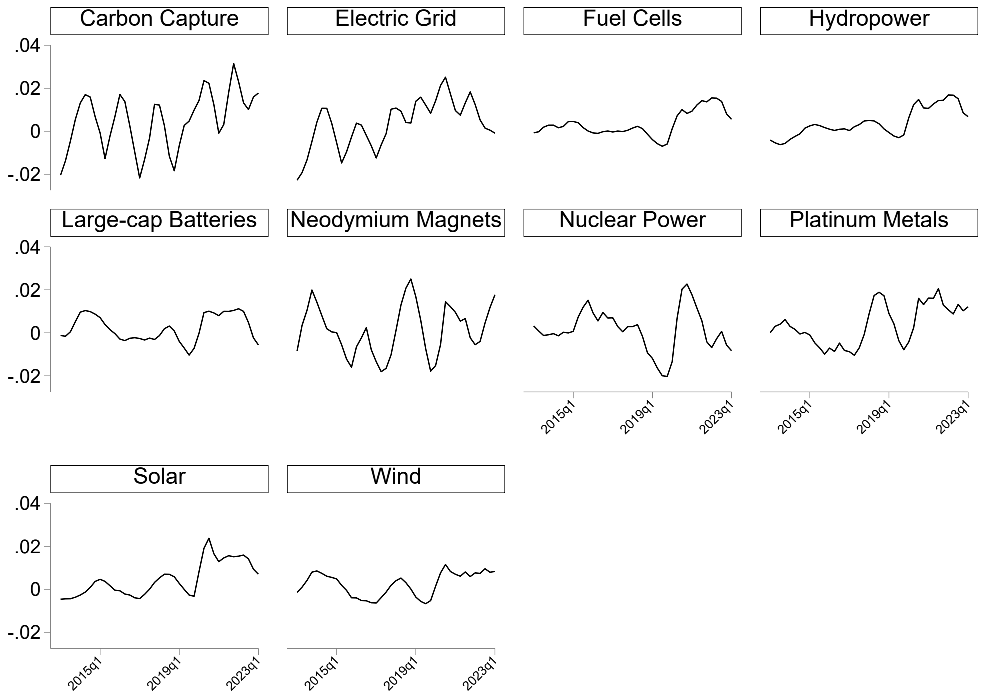
Notes: Figure C7 plots supply disruptions index for Critical Minerals and Materials. For details on index construction, see Section 2.3.

Figure C8: Supply Disruptions Index: Information and Communications Technology



Notes: Figure C8 plots supply disruptions index for Information and Communications Technology subsectors. For details on index construction, see Section 2.3.

Figure C9: Supply Disruptions Index: Energy



Notes: Figure C9 plots supply disruptions index for Energy subsectors. For details on index construction, see Section 2.3.