SUPPLY CHAIN DISRUPTIONS, SUPPLIER CAPITAL,
AND FINANCIAL CONSTRAINTS

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# Supply Chain Disruptions, Supplier Capital, and Financial Constraints*

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**Abstract**

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

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

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# 1 Introduction

Over the last several years, the world has witnessed a significant and troubling rise in supply chain disruptions, making them a critical concern for policymakers in the U.S. and worldwide. The urgency of addressing this issue has been evidenced by recent initiatives aimed at securing supply chains (White House, 2022, 2023). In this paper, we study the impact of supply chain disruptions on firms and investigate the role of financial constraints during such disruptions both empirically and quantitatively.

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

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

In order to understand how firms form trade relationships, we construct a firm-level measure of the total import value accounted for by firms' established trade partners; this metric captures long-term supplier relationships, which we later show are sluggish to adjust. This establishes the supplier base as a state variable for firms, which we refer to as *supplier*

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

*capital*. Given the nature of the data we use (seaborne U.S. imports), this metric specifically represents international supplier capital. We begin by documenting three key empirical facts about the relationship between supplier capital, supply chain disruptions, and firms' financial conditions.

First, the distribution of supplier capital growth rates, which we interpret as supplier capital investment rates, is highly dispersed in the cross-section, roughly five times more dispersed as compared with the distribution of physical capital investment rates. Moreover, supplier capital investment is far less lumpy than physical capital investment. Approximately 40 percent of physical capital investment rates are less than one percent in absolute value, whereas only 8.6 percent of supplier capital investment rates fall within this range. This suggests that the adjustment of supplier capital involves minimal non-convex costs.

Second, we find that supply chain disruptions are associated with lower stock returns and revenue. The results are robust to controlling for firm growth options adjusted for intangible assets (Eisfeldt, Kim and Papanikolaou, 2022), and organizational capital measures (Eisfeldt and Papanikolaou, 2013). Financial conditions play an important role, as stock returns and revenue decline much stronger for financially constrained firms during supply chain disruptions. We consider four common measures of financial constraints—the long-term debt ratio, the Kaplan and Zingales (1997) measure, the Whited and Wu (2006) measure, and a composite measure—and find consistent results across all these metrics.

Third, we document that firms tend to increase their investment in supplier capital following a supply chain disruption. This effect is long-lasting, indicating that it takes firms a considerable amount of time to replenish their supplier capital after experiencing a disruption, and that the adjustment of supplier capital is sluggish. The results are not driven by firm growth options as measured in Eisfeldt, Kim and Papanikolaou (2022) and organizational capital as measured in Eisfeldt and Papanikolaou (2013). We show that the average effect masks substantial cross-sectional heterogeneity: financially constrained firms increase their investment in supplier capital by less. In other words, the accumulation of supplier capital in the aftermath of supply chain disruptions is primarily driven by firms that are not financially constrained.

By construction, our firm-level supply chain disruption index measures the exposure of a firm to supply chain disruptions across product categories. The underlying raw index of disruptions at the product level is unlikely to be driven by the idiosyncratic demand of any given firm. Nevertheless, in order to further alleviate the impact of demand effects, we also provide estimates for a number of IV regressions. Using insights from a well-established literature on trade shocks (e.g., Autor, Dorn and Hanson, 2013; Autor, Dorn, Hanson and Song, 2014), the instrument captures the notion that when a given trade pair is inactive and this coincides with a drop in activity of the foreign shipper with *other* U.S. firms, then the current inactivity of a given trade relationship is likely to be driven by supply considerations rather than a decline in a given firm's demand. Overall, we find that the IV results corroborate our main findings.

Building on our detailed empirical analyses of supply chain relationships, we develop a general equilibrium model with heterogeneous firms. In the model, firms combine physical capital, labor, and intermediate inputs to produce a homogeneous final output. Firms can expand the set of intermediate inputs by making costly investments, and we refer to this set of intermediate inputs a firm has access to as supplier capital. We show that this model is isomorphic to the framework wherein the production function directly features two types of capital stocks—physical capital and supplier capital. In the model, firms operate subject to idiosyncratic, persistent productivity shocks, which result in a cross-sectional distribution of firms. Investment in both capital stocks is subject to adjustment costs, the prevalence of which we parameterize using data on the dispersion of investment rates. Every time period, some fraction of firms receive a supply chain disruption shock in which case a portion of accumulated supplier capital is destroyed. All firms belong to the representative household, which consumes the final goods and supplies labor to firms.

We introduce financial frictions as a working capital constraint in the spirit of Neumeyer and Perri (2005). Specifically, firms must borrow working capital due to a friction in the technology for transferring resources to the households that provide labor services. We then demonstrate that the model can account for the cross-sectional patterns observed in the data. Specifically, the model captures the negative impact of supply chain disruptions on returns and revenue, where the effect is larger for more constrained firms. Moreover, supply chain disruptions lead to a persistent increase in future investment in supplier capital, as firms attempt to restore their capital stock. The effect is smaller for financially constrained firms.

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

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

First, this paper constructs an index of supply chain disruptions at the individual firm level, setting it apart from other measures of supply chain disruptions. Using 200 million individual transactions that comprise the universe of U.S. seaborne imports, we are able to construct an index of supply chain disruptions at an unprecedented level of granularity. In contrast, other supply chain disruption indices are primarily aggregate. The Bloomberg Supply Constraint Indicator is an aggregate index that represents a single common factor extracted from a set of supply-related indicators, including information on supplier deliveries and business backlogs. Global Supply Chain Pressure Index (GSCPI) was designed to measure disruptions in global supply chains based on factors such as supplier delivery times, inventory-to-sales ratios, and transportation costs.[2] The KPMG Supply Chain Stability

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

Index measures how well organizations deal with the ups and downs of market volatility; there are nearly 30 key variables and performance indicators underlying the index.[3] The Flexport Ocean Timeliness Indicator shows the average amount of time is takes cargo to be transported from a factory to its destination port.[4]

On a conceptual level, this paper relates to the literature that considers different types of capital in the production process of firms. Specifically, literature has studied intangible capital (Ai, Croce and Li, 2012; Crouzet, Eberly, Eisfeldt and Papanikolaou, 2022a,b,c; Eisfeldt, Kim and Papanikolaou, 2022), labor capital (Schmidt, 2022), organizational capital (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013, 2014), customer capital and consumer base (Bils, 1989; Herskovic, Kelly, Lustig and Van Nieuwerburgh, 2020). Correspondingly, in our quantitative model, supplier capital is a state variable, and firms endogenously decide how much to invest in it. We use the model to show that these investments are an important margin of adjustment in the aftermath of supply chain disruptions.

We also contribute to the literature on the economics of supply chains and supply chain management. A theoretical body of work examines the formation, stability, and resilience of supply chains (Ostrovsky, 2008; Hatfield, Kominers, Nichifor, Ostrovsky and Westkamp, 2013; Bimpikis, Fearing and Tahbaz-Salehi, 2018; Herskovic, 2018; Kominers, Hatfield, Nichifor, Ostrovsky and Westkamp, 2021; Dew-Becker, Tahbaz-Salehi and Vedolin, 2021; Acemoglu and Tahbaz-Salehi, 2024; Kopytov, Mishra, Nimark and Taschereau-Dumouchel, 2024; Taschereau-Dumouchel, Forthcoming). More broadly, the concept of supplier capital and its accumulation is related to the search-and-match literature (Duffie, Gârleanu and Pedersen, 2005, 2007) and the literature on long-term relationships (Hachem, 2011; Cohen, Hachem and Richardson, 2021). The term "supplier development" was introduced by Leenders (1966) to describe firms' efforts to increase the number of suppliers and improve supplier performance. In the quantitative model we develop in this paper, we conceptualize supplier capital as reflecting the number and size of a firm's suppliers; firms can accumulate this capital over time through costly investments. In this sense, we view the buildup of supplier capital as

[3] https://kpmg.com/p1.

[4] https://www.flexport.com/p1.

one manifestation of supplier development.

A large body of literature studies frictions in financial markets, particularly financial constraints. Several papers propose measures of financial constraints at the firm level (Kaplan and Zingales, 1997; Whited and Wu, 2006). A strand of the literature argues that frictions in financial markets can have significant effects on firm decisions, such as capital investment (Whited, 1992, 2006; Cao, Lorenzoni and Walentin, 2019), labor hiring (Benmelech, Bergman and Seru, 2021), the usage of internal funds (Hennessy and Whited, 2007; Matvos and Seru, 2014; Matvos, Seru and Silva, 2018), complementary services and goods (Hortaçsu, Matvos, Syverson and Venkataraman, 2013), corporate flexibility (Benmelech, Meisenzahl and Ramcharan, 2017; Barry, Campello, Graham and Ma, 2022), leasing (Eisfeldt and Rampini, 2009), and decisions to buy used goods (Eisfeldt and Rampini, 2007). Several papers also identify factors that may influence firm financial constraints (Benmelech and Bergman, 2011; Kermani and Ma, 2023; Lian and Ma, 2021). In this paper, we provide empirical evidence that financially distressed firms tend to invest less in supplier capital and experience larger declines in stock returns and revenue upon receiving a supply chain disruption shock.

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

# 2 Data

In this section, we describe the data we use and lay out the methodology for constructing the two main firm-level measures in the paper—supply chain disruptions and supplier capital.

## 2.1 Overview of the Data

The primary dataset used in this paper is the S&P Global Panjiva, which is a comprehensive bill of lading (BoL) database encompassing more than a billion shipment-level records for cross-border trade transactions. S&P Global Panjiva obtains the BoL information from the U.S. Customs and Border Protection (CBP) through the Freedom of Information Act of 1966 (FOIA). A BoL is a legal document that serves as evidence that a shipment has been transported from its origin to its final destination. Companies are required to complete various fields in each bill of lading, such as shipper (exporter) and consignee (importer) names and addresses, descriptions of goods, vessel name, transport company name, ports of lading (loading) and unlading (unloading), weight and container details. Panjiva also imputes several supplementary variables, such as shipment volume in twenty-foot equivalent units (TEUs) and value in U.S. dollars, based on container information and other shipment attributes.

The raw data for U.S. imports consists of approximately 200 million records, spanning the time period from 2007 to the present. The U.S. data only include seaborne import, and account for about one half of the overall U.S. import.[5] Table C1 in the Appendix provides the description of the key variables available in the data.

## 2.2 Details on Sample Construction

The starting point of the sample construction is the universe of shipments imported by U.S. consignees. We drop observations with missing firm identifier, `conpanjivaid`. Carriers and logistics companies are also excluded since they may be recorded as consignees when handling end-to-end shipments. Specifically, we create 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)

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

for each `conpanjivaid`. Not all consignees can be matched, as many private companies, which are too small for Capital IQ to cover due to insufficient information, engage in global import/export activities. 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 are active for less than 24 months during the sample period are dropped. In order to alleviate redaction concerns, we exclude U.S. firms with high average (per month) shares of missing identifiers for the shipping company—we drop firms if its average share of missing identifiers, `shppanjivaid`, is more than 10 percent. Furthermore, we focus on the time period starting from 2013m1, as earlier data (going back to 2007m1) have a relatively high share of missing US firm identifiers (see Figure C1 in the Appendix).

## 2.3 Construction of the Supply Chain Disruption Index

### 2.3.1 Methodology

Our primary objective is to construct an index of supply chain disruptions at the *firm*-level. Conceptually, we measure supply chain disruptions as a fraction of established trade pairs that are temporarily inactive. We focus on temporary disruptions rather than permanent dissolution of trade pairs, as the latter is typically driven by fundamental forces unrelated to supply chain-specific factors.

We first construct an index of supply chain disruptions for each HS 2-digit product category utilizing the entire dataset and then average those indices for each ultimate parent firm using fractions of the total firm-level import value accounted for by individual HS 2-digit product codes as weights. Specifically, an index of supply chain disruptions for firm $i$ at time

$t$ is

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

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

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

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

**Discussion.** Even though it is feasible to construct an index of supply chain disruptions directly on a firm-by-firm basis, we do not pursue this approach in this paper for two reasons. First, our firm-level index of supply chain disruptions reflects, by construction, a firm's exposure to supply chain disruptions across product categories. In other words, our index of disruptions is unlikely to be driven by the idiosyncratic demand of a given firm, as a single firm's idiosyncratic demand may have little impact on the overall product category. Nevertheless, to further alleviate the impact of demand effects, we also provide results from a number of IV regressions in the section with empirical results (see Section 3 for details) and show that these regressions deliver qualitatively similar but quantitatively stronger results as compared to OLS regressions.

Second, we find that indices constructed directly at the firm level are noisy for a large number of public firms that have few trading partners. Our approach, on the other hand, can be consistently applied to the vast majority of public companies. Moreover, we confirmed that, for a subset of public firms with a sufficiently large number of suppliers, the index constructed using firms' exposure to various product categories is strongly positively correlated with the index computed directly on a firm-by-firm basis.

### 2.3.2 HS 2-digit Supply Chain Disruptions

We next describe how we construct the HS 2-digit supply chain disruption indices, $\widehat{\text{Index}}_{jt}$. We define the disruption rate for the HS 2-digit product category $j$ at time $t$ as the fraction of *established* trade partners (defined as firm-pairs that trade regularly) that *temporarily* cease trading activities:

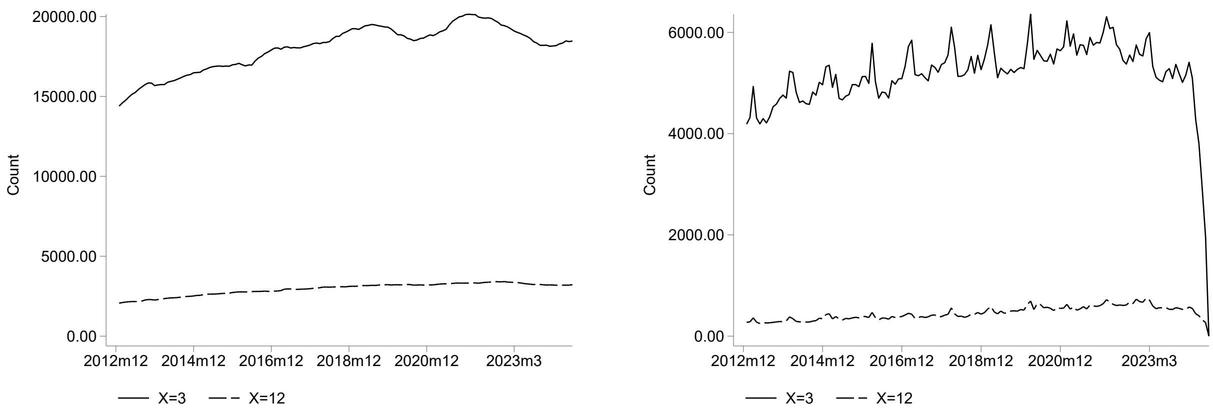
$$\text{Disruption rate}_{jt}(X,p,v) = \frac{|\{\text{established}(X,p) \cap \text{inactive} \cap \text{active in future}(v)\}_{jt}|}{|\{\text{established}(X,p)\}_{jt}|}. \quad (3)$$

A trade pair is established at time $t$ if the pair has actively traded for $X$ months over a consecutive 12-month period before time $t$ and if the pair has been active at least once between $t-p$ and $t-1$. The disruption rate is the fraction of established pairs that are inactive at time $t$ but become 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. The tuning parameters are $X \in \{3,6,9,12\}$, $p \in \{12,24,36\}$ and $v \in \{1,2,6,12\}$ that we discuss below.

The tuning parameter $X$ determines how frequently a trade pair needs to be active for us to classify it as being established. A higher value of $X$ results in fewer trade pairs being classified as established. We consider three different horizons over which we assess whether a 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 C5 in the Appendix). Finally, in determining whether trade pairs become active in the future, we consider the following horizons: $v \in \{1,2,6,12\}$.

In order to give a sense of what accounts for the time-series behavior of the disruption rate, Figure 1 plots the time series for the numerator and the denominator of Equation (3) ($X = 3$ or 12, $p = 12, v = 6$ for HS code 39 (plastics)). Panel (A) demonstrates that the

Figure 1: Time-Series Behavior of Index Components




(A) Established and recently active

(B) Temp. inactive established

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

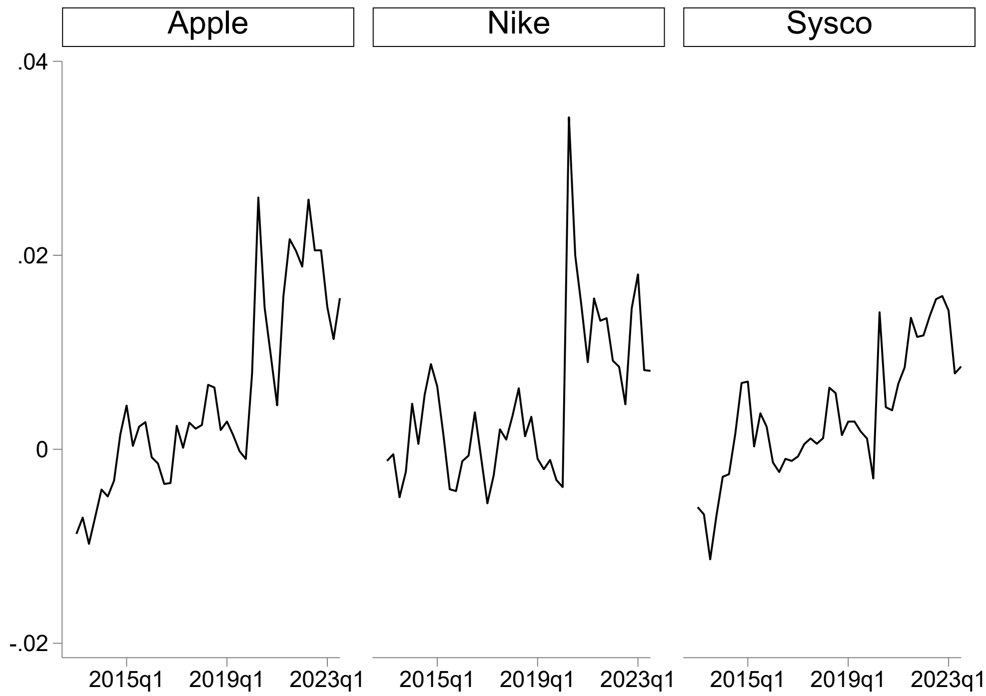
number of established and recently active trade pairs is smooth; as the requirement for being established becomes more conservative ($X$ rises), the denominator of (3) declines. In turn, Panel (B) shows that the number of temporarily inactive trade pairs is volatile and exhibits seasonality.

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

**End-of-sample Treatment** Since our definition of the disruption rate includes the notion of temporarily inactive trade pairs, the identification of disrupted trade pairs becomes challenging toward the end of the sample as we do not observe which inactive pairs will become

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

Figure 2: Firm-Level Disruptions: Select Firms




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

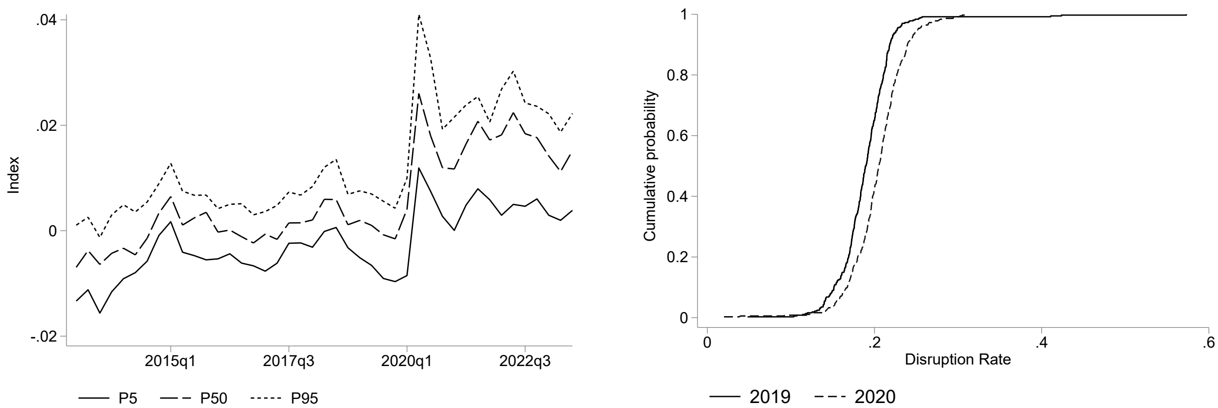
active again. This issue is illustrated by the right panel of Figure 1, where the number of temporarily inactive trade pairs falls to zero as it gets closer to the end of the sample time period.

One can, in principle, impute the number of inactive trade pairs that eventually recover by exploiting the very stable relative recovery rates of trade pairs over various horizons (see Figure C2 in Appendix for an illustration and Liu, Smirnyagin and Tsyvinski 2023 for details). In this paper, we do not use an imputation scheme and our supply chain disruption index is not available for the last 12 months of the sample period.

### 2.3.3 Firm-level Supply Chain Disruptions Index

Our firm-level supply chain disruption index is the weighted average of HS 2-digit product-level indicies $\widehat{\text{Index}}_{jt}$. The index has monthly frequency; we aggregate it to quarterly fre-

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




(A) Firm-Level Disruptions: Percentiles (B) CDF of Disruption Rates

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

quency when we merge it with the Compustat extract. Figure 2 plots the quarterly index of firm-level supply chain disruptions for several selected public firms in the sample: Apple, Nike, and Sysco. The numbers on the vertical axis show the change in the share of temporarily inactive established trade pairs relative to the historical (pre-2020) average.

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

Panel (A) of Figure 3 shows the time-series evolution of percentiles in the firm-level index distribution over the sample period. Several observations stand out. First, the cross-sectional distribution of disruptions was relatively concentrated prior to 2020, with the P5-P95 range of about 1pp. Following an overall increase in disruptions in 2020 (illustrated in Panel (B)), the distribution spread considerably, with the P5-P95 range reaching 3pp.

In subsequent years, the average level of disruptions decreased, though overall dispersion persisted, reflecting the ongoing pressures that some firms continue to face in their supply chains. Notably, the bottom five percent of firms in terms of supply chain pressures saw a near-complete normalization of conditions in 2021.

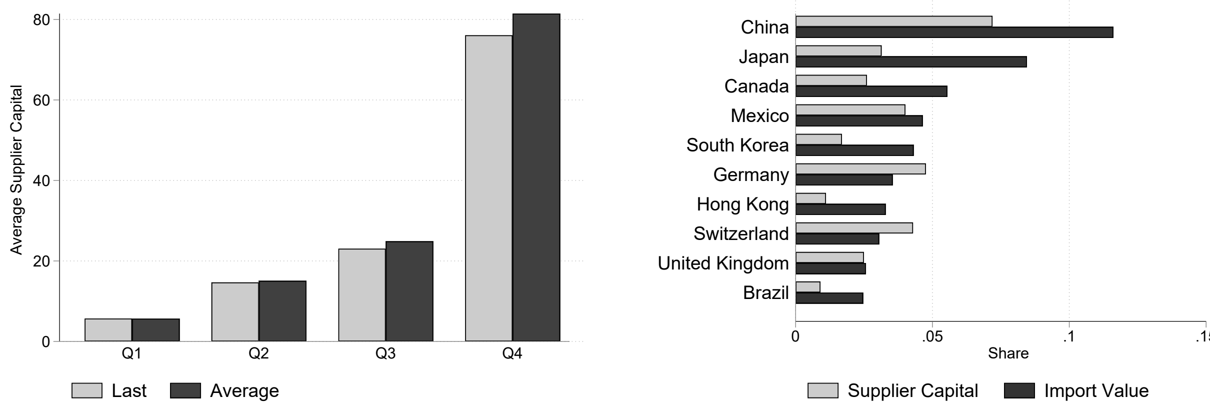
## 2.4 Measuring Supplier Capital

The other main measure we construct in the paper is firm-level supplier capital. In line with measuring supply chain disruptions as a fraction of established trade pairs that are temporarily inactive, we measure firm's international supplier capital as the total import value in U.S. dollars accounted for by established trade partners with whom the firm recently traded. This metric, therefore, captures both the number of established trade partners and their importance in terms of trade value. We choose the tuning parameters as $X = 3$ and $p = 24$; that is, trade occurred with that partner in at least 3 months over a 12-month period, and we recorded at least one trade of that pair over the preceding 24 months. We use this set of relatively lenient tuning parameters to maximize our sample size, since there is a sizable fraction of firms that only have a limited number of suppliers for larger values of $X$ and would have otherwise been dropped from our final sample.

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

Figure 4 demonstrates how supplier capital is related to both the number of established trade partners and the total import value. Panel (A) plots the average supplier capital by quantile of the number of established trade partners. The distribution of the number of established trade partners is highly right-skewed, with the $25^{th}, 50^{th}$, and $75^{th}$ percentiles being 6, 15, and 37, respectively. The panel demonstrates that firms with a larger number of

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




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

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

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

established trade partners import more from them. Even though these two metrics are highly correlated, we measure supplier capital using monetary value, since it captures not only the number but also the relative importance of established trade partners. Lastly, the figure shows that the difference in how supplier capital is measured—whether using the value from the last transaction or the average value over the last 24 months—is minimal. Throughout the paper, we use the value from the last transaction.

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

## 2.5 Summary Statistics

Table 1 provides summary statistics for three selected quarters: 2019Q1, 2020Q1, and 2021Q1.[7] The size distribution of firms in our sample is right-skewed, with the $90^{th}$ percentile of any common size metric (physical capital, employment, assets and sales) being much further from the median as compared with the difference between the median and the $10^{th}$ percentile. As per firm-level supply chain disruptions, we see a dramatic increase in the average index between 2020Q1 and 2021Q1 (from 0.3pp to 1.1pp). At the same time, the cross-sectional dispersion in the index has also risen over that time period, mirroring the patterns depicted in Figure 3.

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

# 3 Empirical Results

In this section, we empirically study the relationship between supplier capital, supply chain disruptions, and financial constraints. We structure our findings around three key facts.

**Fact 1: The distribution of supplier capital investment rates, as measured by supplier capital growth rates, is highly dispersed. Moreover, there is little evidence of excess lumpiness in supplier capital investment.**

We examine the distribution of investment rates in supplier capital, as measured by the log change of supplier capital of firm $i$ at time $t$, $\Delta \log m_{i,t}$. Panel (A) of Figure 5 shows that the distribution is highly dispersed, with an interdecile range of 0.80 and a standard

[7] Since many public firms have few trading partners (see Figure C3 in Appendix), in our subsequent analysis we focus on the set of Compustat firms with at least 50 unique suppliers.

Table 1: Summary Statistics: Select Quarters

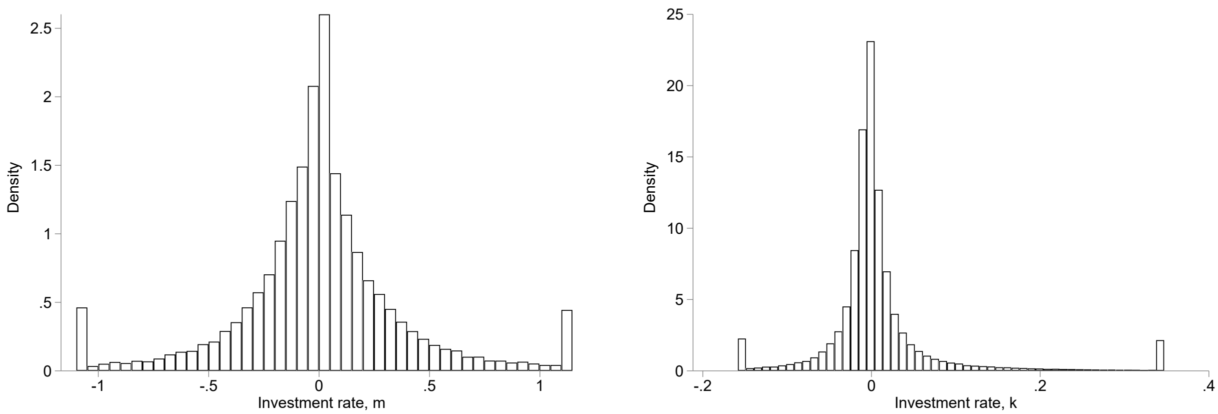
| Variable | Obs. | Mean | Std. Dev. | P10 | P50 | P90 |
|---|---|---|---|---|---|---|
| **2019Q1** | | | | | | |
| Capital (Log) | 3738 | 5.094 | 3.559 | 0.235 | 5.494 | 9.323 |
| Sup. Capital (Log) | 846 | 1.265 | 2.295 | -1.689 | 1.305 | 3.929 |
| Employment (Log) | 3319 | 0.174 | 2.867 | -3.990 |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

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

deviation of 0.38. For comparison, Panel (B) plots the distribution of physical capital growth rates, which exhibits significantly smaller dispersion, with an interdecile range of 0.10 and a standard deviation of 0.07.

Importantly, supplier capital growth rates are far less lumpy than those of physical capital. Physical capital exhibits a high degree of lumpiness (Cooper and Haltiwanger, 2006; Bai, Li, Xue and Zhang, 2022), with approximately 40 percent of observations being less than one percent in absolute value, whereas the corresponding number for supplier capital is

FIGURE 5: DISTRIBUTIONS OF CAPITAL GROWTH RATES




(A) Supplier capital

(B) Physical capital

*Notes:* Figure 5 consists of two panels. Panel (A) plots distribution of supplier capital growth rates $\Delta \log m$; Panel (B) plots distribution of physical capital growth rates $\Delta \log k$. The data are winsorized at 1 and 99 percentiles.

only 8.6 percent. This observation suggests that the adjustment of supplier capital involves minimal non-convex costs.

**Fact 2: Supply chain disruptions are associated with lower stock returns and revenue; the effect is more pronounced for financially constrained firms.**

In the next set of results, we evaluate the impact of supply chain disruptions on firm returns and revenue. In particular, we study whether stock returns and firm revenue are affected by contemporaneous supply chain disruptions.

Columns (1)–(4) in Table 2 report results for stock returns, while columns (5)–(8) show results for firm revenue. Provided that we aim to examine how current-period supply chain disruptions affect firm returns and revenue, we use changes in our supply chain disruption index, denoted as $\Delta$Index, as the main independent variable. For each dependent variable, we gradually include additional controls. Columns (1) and (5) only include time fixed effects. Columns (2) and (6) include both time and firm fixed effects. Columns (3) and (7) further include a measure of supplier concentration and a measure of relationship strength,

TABLE 2: SUPPLY CHAIN DISRUPTIONS AND FIRMS' REVENUE AND RETURNS

| | Returns | | | | Revenue | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ΔIndex | -0.16** | -0.15* | -0.15* | -0.16* | -0.28*** | -0.14*** | -0.14*** | -0.24*** |
| | (0.08) | (0.08) | (0.08) | (0.09) | (0.07) | (0.04) | (0.04) | (0.05) |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Firm FE | N | Y | Y | Y | N | Y | Y | N |
| Controls | N | N | N | Y | N | N | N | Y |
| $R^2$ | 0.20 | 0.24 | 0.24 | 0.25 | 0.01 | 0.84 | 0.84 | 0.90 |
| $N$ | 229,668 | 229,663 | 229,663 | 163,737 | 86,456 | 86,382 | 86,382 | 50,650 |

*Notes:* Table 2 reports OLS estimates of the following equation:

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

where the left-hand side variable is either firm revenue or stock returns. *Returns* is the logarithm of the stock returns. *Revenue* is constructed as firm revenue divided by total assets. Results for *Returns* are at the monthly level and results for *Revenue* are at the quarterly level. Both variables are multiplied by 100 to facilitate interpretation. ΔIndex represents the changes in the (standardized) disruption index. Columns (3), (4), (7), and (8) include lagged supplier concentration and lagged relationship strength as controls. Controls include the lagged logarithm of firm size, lagged market-to-book ratio, lagged net price margin, and lagged accrual. Standard errors are clustered at the firm level. All variables are winsorized at the top and bottom 1 percent. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

as proposed by the management literature on supply chains, as additional controls.[8] Finally, columns (4) and (8) are the tightest specifications we consider, whereby we further include firm size, market-to-book ratio, net price margin, and accrual as controls.

The point estimates of ΔIndex are consistently negative and significant at the 1 percent level, suggesting that supply chain disruptions are associated with lower revenue and stock returns. The estimates are also economically meaningful. In our preferred specifications with full controls (columns (4) and (8)), the results indicate that a one standard deviation increase in the supply chain disruption index is associated with a 0.6 and a 1.0 percent decrease in the standard deviation of stock return and revenue, respectively.

In our baseline analyses above, we control for the market-to-book ratio to account for

[8]The management literature on supply chains has proposed several firm-level metrics of supply chain management. We construct and control for two commonly used metrics—supplier concentration and a measure of relationship strength—to establish the robustness of our results to these measures of firms' supply chain management strategies. Details on how we construct these measures are provided in Appendix A.1.

Table 3: Supply Chain Disruptions and Firms' Revenue and Returns: Role of Financial Constraints

| | Returns | | | | Revenue | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta$Index $\times$ LT$_{t-1}$ | -0.10** | | | | -0.09*** | | | |
| | (0.05) | | | | (0.03) | | | |
| $\Delta$Index $\times$ KZ$_{t-1}$ | | -0.13*** | | | | -0.07** | | |
| | | (0.05) | | | | (0.03) | | |
| $\Delta$Index $\times$ WW$_{t-1}$ | | | -0.16* | | | | -0.17** | |
| | | | (0.09) | | | | (0.07) | |
| $\Delta$Index $\times$ Comp$_{t-1}$ | | | | -0.13*** | | | | -0.05** |
| | | | | (0.05) | | | | (0.03) |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.25 | 0.25 | 0.25 | 0.25 | 0.90 | 0.90 | 0.90 | 0.90 |
| $N$ | 162,683 | 163,585 | 163,600 | 162,706 | 50,349 | 50,649 | 50,650 | 50,362 |

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

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

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

firm growth options. Recent literature argues that it is important to account for intangible capital when constructing market-to-book ratio (e.g., Eisfeldt, Kim and Papanikolaou, 2022). In columns (1) and (2) of Table C3 in the Appendix, instead of controlling for the standard market-to-book ratio, we redo the analyses by controlling for the market-to-book ratio adjusted for intangible capital (Eisfeldt, Kim and Papanikolaou, 2022) and the organizational capital measure (Eisfeldt and Papanikolaou, 2013). We find results that are qualitatively similar to our baseline specifications.

We next study the role of financial constraints in affecting the relationship between returns/revenue and supply chain disruptions. We use three common measures in the literature to gauge whether firms are financially constrained: the long-term debt ratio (LT), the Kaplan and Zingales (1997) measure (KZ), and the Whited and Wu (2006) measure (WW). We also construct a composite measure (Comp) as the average of the standardized LT, KZ, and WW. For each period, we divide each of the four measures into five quintile brackets, using bracket numbers as corresponding variables. Firms with the lowest values are placed in bracket 1, while those with the highest values are placed in bracket 5. Consequently, higher values indicate that companies are more financially constrained.

We estimate different versions of the following model:

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

where $FC$ is one of the four financial constraint measures, and $\mathbf{X}_{it-1}$ is a vector of controls including $FC$ itself as well as interactions between the controls and $\Delta\text{Index}_{it}$.

Table 3 reports our results. We find that the interaction terms between ΔIndex and each measure of financial constraints considered are consistently negative and, in most cases, significant at least at the 5 percent level. The economic magnitudes are sizable, with the point estimates of the interaction terms being similar in magnitude to baseline results. Overall, these findings suggest that the revenue and stock returns of more financially constrained firms decline more sharply during supply chain disruptions.

**Fact 3: Supply chain disruptions are associated with a positive future investment in supplier capital; the effect is less pronounced for more financially constrained firms.**

We now study the effect of supply chain disruptions on firm investment in supplier capital. Our key independent variable is the firm-level supply chain disruption index, $\text{Index}_{it}$, which summarizes the cumulative supply chain disruptions experienced by a company. In our specifications, we project supplier capital investment rates over different horizons on $\text{Index}_{it}$.

Table 4 reports the results for cumulative supplier capital investment rates measured up to four quarters ahead. All specifications include the current level of firms' supplier capital as a control. The point estimates on $\text{Index}_{it}$ are consistently positive and mostly statistically significant, indicating that companies increase investment in supplier capital when they experience supply chain disruptions. Additionally, the coefficient estimates tend to increase at longer horizons, indicating that the adjustment of supplier capital is sluggish and it takes firms time to fully replenish their supplier capital. In columns (3) to (5) of Table C3 in the Appendix, instead of controlling for the standard market-to-book ratio, we redo the analyses by controlling for the market-to-book ratio adjusted for intangible capital (Eisfeldt, Kim and Papanikolaou, 2022) and the organizational capital measure (Eisfeldt and Papanikolaou, 2013). We find that the results are similar to our baseline specifications, which we take as evidence that our findings are not driven by firm growth options.

Additionally, in Appendix A.3, we study the effect of supply chain disruptions on firms' physical capital investments, $\Delta_t^{t+k} \log k_i$, which represents the log change in the book value of the tangible capital stock of firm $i$ between times $t$ and $t+k$. We find a negative and statistically significant effect, especially over longer time horizons.

Next, we study the role of financial constraints in firms' ability to restore supplier capital following supply chain disruptions. In order to assess the effect of financial constraints, we use four measures: firms' long-term debt ratio (LT), the Kaplan-Zingales (KZ) index, the Whited-Wu (WW) index, and a composite measure. We estimate different versions of the following model:

$$\Delta_t^{t+k} \log m_i = \beta_0 \text{Index}_{it} + \beta_1 \text{Index}_{it} \times FC_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{5}$$

where $FC$ is one of the four financial constraint measures and $\mathbf{X}_{it-1}$ is a vector of controls that includes year-quarter and firm fixed effects, as well as the lagged measure of financial constraint, lagged logarithms of the firm's physical and supplier capital stocks, among others. The coefficient of interest is $\beta_1$ which measures the interaction effect of supply chain

Table 4: Supply Chain Disruptions and Firm Investment in Supplier Capital

| | $\Delta_t^{t+1}\log m$ | | | $\Delta_t^{t+2}\log m$ | | | $\Delta_t^{t+4}\log m$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Index | 1.63** | 1.40** | 1.42** | 2.15* | 1.73 | 1.78 | 3.80** | 3.23** | 3.32** |
| | (0.65) | (0.65) | (0.65) | (1.10) | (1.08) | (1.08) | (1.65) | (1.64) | (1.63) |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | N | N | Y | N | N | Y | N | N | Y |
| $R^2$ | 0.07 | 0.07 | 0.08 | 0.12 | 0.12 | 0.13 | 0.21 | 0.22 | 0.22 |
| $N$ | 21,497 | 21,497 | 21,497 | 21,410 | 21,410 | 21,410 | 20,692 | 20,692 | 20,692 |

*Notes:* Table 4 reports OLS estimates. The dependent variable is investment rate into supplier capital $\Delta_t^{t+k}\log m$ where $k \in \{1, 2, 4\}$. *Index* is a firm-level index of supply chain disruptions constructed in Section 2.3. All specifications control for lagged $\log m$. Columns (2), (3), (5), (6), (8), and (9) include lagged supplier concentration and lagged relationship strength as controls. Controls include lagged logarithm of supplier concentration, lagged relationship strength, firm size, lagged market-to-book ratio, lagged net price margin, lagged accrual, and lagged logarithm of physical capital. Standard errors are clustered at the firm level. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

disruptions with a financial position of the firm.

Table 5 reports the results. The table reveals substantial heterogeneity in responsiveness to supply chain disruption shocks among firms with different levels of financial constraints. The interaction terms with firm financial constraints are predominantly negative across different horizons. The point estimates of the interaction term with the composite measure are consistently negative and significant at the 5 percent level. Furthermore, the magnitude of these estimates tends to increase at longer horizons, accompanied by rising statistical significance. We interpret this as evidence of the dynamic nature of investment decisions and the persistent effect of financial conditions on future investments in supplier capital. These results demonstrate that the positive average effect reported in Table 5 is primarily driven by firms that are not financially constrained.

**Controlling for Demand.** By construction, our firm-level index of supply chain disruptions measures the exposure of a firm to supply chain disruptions across product categories. In other words, the underlying raw index of disruptions at the product level is unlikely to

Table 5: Supply Chain Disruptions and Firm Investment in Supplier Capital: Role of Financial Constraints

| | $\Delta_t^{t+1} \log m$ | | | | $\Delta_t^{t+2} \log m$ | | | | $\Delta_t^{t+4} \log m$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Index × $\text{LT}_{t-1}$ | -0.40* | | | | -1.08*** | | | | -1.32** | | | |
| | (0.22) | | | | (0.37) | | | | (0.66) | | | |
| Index × $\text{KZ}_{t-1}$ | | -0.37 | | | | -1.21*** | | | | -1.84*** | | |
| | | (0.23) | | | | (0.39) | | | | (0.69) | | |
| Index × $\text{WW}_{t-1}$ | | | -0.32 | | | | -0.00 | | | | 0.83 | |
| | | | (0.45) | | | | (0.63) | | | | (0.90) | |
| Index × $\text{Comp}_{t-1}$ | | | | -0.47** | | | | -1.05*** | | | | -1.58** |
| | | | | (0.21) | | | | (0.35) | | | | (0.63) |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.08 | 0.08 | 0.08 | 0.04 | 0.04 | 0.04 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| $N$ | 21,454 | 21,456 | 21,496 | 21,472 | 21,367 | 21,409 | 20,651 | 20,691 | 20,668 | 20,601 | 20,602 | 20,603 |

*Notes:* Table 5 reports OLS estimates of the following equation:

$$\Delta_t^{t+k} \log m = \beta_0 \text{Index}_{it} + \beta_1 \text{Index}_{it} \times FC_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}.$$

The dependent variable is investment rate into supplier capital $\Delta_t^{t+k} \log m$ where $k \in \{1, 2, 4\}$. Dependent variables are multiplied by 100 to facilitate interpretation. Index represents the standardized supply chain disruption index, and $FC_{it-1}$ is a measure of financial constraints. LT, KZ, WW, and Comp are the bracket numbers of assigned quantile brackets based on the long-term debt ratio, the Kaplan and Zingales (1997) measure, the Whited and Wu (2006) measure, and a composite measure, respectively. Controls include the lagged versions of the logarithm of supplier concentration, relationship strength, firm size, market-to-book ratio, net price margin, accrual, as well as cross-terms between each of these variables and ΔIndex. Standard errors are clustered at the firm level. All variables are winsorized at the top and bottom one percent. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

be driven by the idiosyncratic demand of any given firm, since it incorporates information across a broad set of firms. Nevertheless, in order to further alleviate the impact of demand effects, we also provide estimates for a number of IV regressions. Using insights from a well-established literature on trade shocks (e.g., Autor, Dorn and Hanson, 2013; Autor, Dorn, Hanson and Song, 2014), we construct our instrument based on the number of U.S. firms with which the established foreign shippers of a given U.S. firm trade in a given time period, excluding the focal U.S. firm (see Appendix A.3 for details). We conduct these calculations at the firm level within each product category and subsequently aggregate them to the firm-quarter level using firm import values at the product level as weights. Intuitively, this instrument is designed to capture the notion that when a given U.S. firm is inactive, and this inactivity coincides with a drop in activity among that U.S. firm's established shippers, it is likely that the inactivity is driven by supply considerations rather than a decline in the given firm's demand.

Table A1 in the Appendix reports the results. Overall, we find that the IV estimates are qualitatively similar to those reported in Tables 4 and 5: investment in supplier capital increases upon receiving a shock, and the response is weaker for more financially constrained firms.

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

# 4 Model

In this section, we develop a model of supplier capital formation in an environment with supply chain disruptions.[9] Our model accounts for the empirical findings reported in Section 3. Specifically, the model explains the positive investment response in supplier capital and the negative response in physical capital following a supply chain disruption shock. By way of introducing a financial constraint into the model, we highlight its importance in accounting for the heterogeneous investment response across firms. Importantly, we use the model to demonstrate that firms' ability to accumulate supplier capital through costly investment is

[9]There is a growing literature studying aggregate effects of supply chain disruptions (e.g., Bonadio, Huo, Levchenko and Pandalai-Nayar, 2021; Alessandria, Khan, Khederlarian, Mix and Ruhl, 2023; Acharya, Crosignani, Eisert and Eufinger, 2023; Heise, Pierce, Schaur and Schott, 2024; Amiti, Itskhoki and Weinstein, 2024). An influential related strand of the literature theoretically studies the formation, fragility and failures in supply networks (e.g., Ostrovsky, 2008; Elliott, Golub and Jackson, 2014; Ambrus and Elliott, 2021; Elliott, Golub and Leduc, 2022; Acemoglu and Tahbaz-Salehi, 2024). Our paper is the first to measure supply chain disruptions at the individual firm level and study the impact of those disruptions on firm-level outcomes both empirically and quantitatively.

a crucial margin of adjustment in the aftermath of supply chain disruptions shocks.

## 4.1 Environment

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

**Technology** Every firm $i$ has access to the following production technology:

$$\widetilde{y}(k,\widetilde{m},\widetilde{z},n) = e^{\widetilde{z}}k^{\widetilde{\theta}}n^{\widetilde{\alpha}}\left[\left(\int_0^{\widetilde{m}} x\left(\nu\right)^{\frac{\sigma-1}{\sigma}}\mathrm{d}\nu\right)^{\frac{\sigma}{\sigma-1}}\right]^{\widetilde{\phi}} \tag{6}$$

with $\widetilde{\theta},\widetilde{\alpha},\widetilde{\phi} > 0$ and $\sigma \in (0,1)$. Firms combine physical capital $k$, labor $n$ along with intermediate inputs $x(\nu)$ to produce the gross output $\widetilde{y}$. Variable $\widetilde{m}$ in Equation (6) denotes supplier capital, i.e. the mass of input varieties the producer has access to. The production function is scaled by an idiosyncratic productivity component $\widetilde{z}$.

Each intermediate input $x\left(\nu\right)$ comes at a marginal cost $p$. We define firm's revenue net of input costs as

$$r(k,\widetilde{m},\widetilde{z},n) = \max_{x(\nu)} e^{\widetilde{z}}k^{\widetilde{\theta}}n^{\widetilde{\alpha}}\left[\left(\int_0^{\widetilde{m}} x\left(\nu\right)^{\frac{\sigma-1}{\sigma}}\mathrm{d}\nu\right)^{\frac{\sigma}{\sigma-1}}\right]^{\widetilde{\phi}} - \int_0^{\widetilde{m}} px\left(\nu\right)\mathrm{d}\nu. \tag{7}$$

Formulation in Equation (7) is equivalent to:

$$r(k,\widetilde{m},\widetilde{z},n) = \max_{X} e^{\widetilde{z}}k^{\widetilde{\theta}}n^{\widetilde{\alpha}}X^{\widetilde{\phi}} - PX, \tag{8}$$

where $X = \left(\int_0^{\widetilde{m}} x\left(\nu\right)^{\frac{\sigma-1}{\sigma}}\mathrm{d}\nu\right)^{\frac{\sigma}{\sigma-1}}$ and $P$ is the cost index of intermediate inputs:

$$P \equiv \min_{x(\nu)} \int_0^{\widetilde{m}} px\left(\nu\right)\mathrm{d}\nu \qquad \text{subject to } \left(\int_0^{\widetilde{m}} x\left(\nu\right)^{\frac{\sigma-1}{\sigma}}\mathrm{d}\nu\right)^{\frac{\sigma}{\sigma-1}} = 1.$$

Because of the symmetry, it follows that $x(\nu) = x$ for all varieties $\nu$. Thus, $P = \widetilde{m}px$ and $\widetilde{m}^{\frac{\sigma}{\sigma-1}}x = 1$, implying that $P = p\widetilde{m}^{-\frac{1}{\sigma-1}}$. With this, we can rewrite firm's revenue net of input costs $r(k, \widetilde{m}, \widetilde{z}, n)$ as follows:

$$r(k, \widetilde{m}, \widetilde{z}, n) = \max_{X} e^{\widetilde{z}} k^{\widetilde{\theta}} n^{\widetilde{\alpha}} X^{\widetilde{\phi}} - p\widetilde{m}^{-\frac{1}{\sigma-1}} X. \tag{9}$$

The first-order condition for (9) implies that $X = \left(\frac{e^{\widetilde{z}} k^{\widetilde{\theta}} n^{\widetilde{\alpha}} \widetilde{\phi} \widetilde{m}^{\frac{1}{\sigma-1}}}{p}\right)^{\frac{1}{1-\widetilde{\phi}}}$. Thus,

$$r(k, \widetilde{m}, \widetilde{z}, n) = \left(e^{\widetilde{z}} k^{\widetilde{\theta}} n^{\widetilde{\alpha}}\right)^{\frac{1}{1-\widetilde{\phi}}} \left(\widetilde{\phi}^{\frac{\widetilde{\phi}}{1-\widetilde{\phi}}} - \widetilde{\phi}^{\frac{1}{1-\widetilde{\phi}}}\right) \left(\frac{\widetilde{m}^{\frac{1}{1-\sigma}}}{p}\right)^{\frac{\widetilde{\phi}}{1-\widetilde{\phi}}}. \tag{10}$$

According to Equation (10), the firm's revenue net of input costs is a power function of a composite variable $m := \frac{\widetilde{m}^{\frac{1}{1-\sigma}}}{p}$, which depends on supplier capital, $\widetilde{m}$, and the marginal cost of intermediate goods, $p$. In what follows, we refer to $m$ as supplier capital, with the understanding that shocks to supplier capital can arise through changes in $\widetilde{m}$—i.e., the mass of input varieties the producer has access to—or through input prices, $p$, or both. This resonates with our empirical measure of supplier capital, i.e., the import value sourced from the set of established suppliers.

In the subsequent analysis we directly work with the *value-added* function $y(k, m, z, n)$ in which intermediate inputs do not directly enter the production function:

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

where $z := \frac{\widetilde{z}}{1-\widetilde{\phi}}$, $\kappa\theta = \frac{\widetilde{\theta}}{1-\widetilde{\phi}}$, $\kappa\alpha = \frac{\widetilde{\alpha}}{1-\widetilde{\phi}}$, $\kappa\phi = \frac{\widetilde{\phi}}{1-\widetilde{\phi}}$ and $\alpha = 1 - \theta - \phi$. Parameter $\kappa$ has an interpretation of returns to scale. The scaling constant $\left(\widetilde{\phi}^{\frac{\widetilde{\phi}}{1-\widetilde{\phi}}} - \widetilde{\phi}^{\frac{1}{1-\widetilde{\phi}}}\right)$ is common across firms and is dropped from the subsequent analysis.

Idiosyncratic component $z$ follows an AR(1) process with the persistence parameter $\rho_z \in (0, 1)$:

$$z_{t+1} = \rho_z z_t + \varepsilon^{z}_{t+1}, \quad \varepsilon^{z}_{t+1} \sim \mathcal{N}(0, \sigma_z) \tag{11}$$

**Labor** The labor market is frictionless with the wage rate $W$.

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

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

## 4.2 Firm Optimization

The aggregate state at time $t$ consists of the distribution of firms over the idiosyncratic states $\mu = \mu(k, m, z)$, as well as the value of the aggregate supply chain disruption shock $\zeta_t$. 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 $(k, m, z)$:

$$v_t(k, m, z) = p^{shock} v_t^{cont}(k, \zeta_t m, z) + (1 - p^{shock}) v_t^{cont}(k, m, z). \tag{12}$$

According to Equation (12), with i.i.d. probability $p^{shock}$ firms receive a supply chain 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 $\zeta_t$ governs the severity of a supply chain disruption event.

Value function $v_t^{cont}$ in Equation (12) describes the intertemporal choices of the firm:

$$v_t^{cont}(k,m,z) = \pi_t(k,m,z) + \max_{k',m'\geq 0} \left\{-i_k(k',k) - i_m(m',m) + \mathbb{E}_t\left[M_{t+1}v_{t+1}(k',m',z')\right]\right\}, \tag{13}$$

where firm's operating profits $\pi$ are defined as:

$$\pi_t(k,m,z) = \max_{n\geq 0} e^z \left(k^\theta m^\phi n^{1-\theta-\phi}\right)^\kappa - W_t n - \underbrace{[R_{t-1}-1]\eta W_t n}_{\text{net interest on borrowing}} \tag{14}$$

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

In Equation (13), $i_x, x \in \{k, m\}$ denote investments into two types of capital:

$$i_x = x' - (1-\delta_x)x + AC(x',x), \tag{15}$$

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

Finally, firm's dividends are defined as:

$$Div_t(k,m,z) := \pi_t(k,m,z) - i_k(k',k) - i_m(m',m). \tag{16}$$

## 4.3 Household Optimization

The representative household maximizes the discounted stream of utilities subject to the budget constraint. We assume that labor is supplied inelastically, and it is normalized to be 1. The wealth is held in one-period firm shares, $\xi_t(k,m,z)$. The price of current shares is $\omega_0$, and the purchase price of new shares is $\omega_1$. The household's dynamic programming problem is:

$$H_t = \max_{c,\xi'} \left[U(c) + \beta \mathbb{E}_t H_{t+1}\right] \tag{17}$$

subject to

$$c + b' + \int \omega_{1,t}(k', m', z') \mathrm{d}\xi_{t+1} \leq W_t + R_t b + \int \omega_{0,t}(k, m, z) \mathrm{d}\xi_t. \tag{18}$$

The right-hand side of (18) represents the resources available to the household; it consists of firm shares from the previous period, as well as labor income and return on bonds. Part of these resources is consumed, and the rest is reinvested into firm shares and a risk-free bond.

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

## 4.4 Parameterization and Model Fit

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

We set the depreciation rate $\delta$ to match the average quarterly investment rate in the data (0.01). Quadratic adjustment costs are set to match the dispersion of investment rates in the cross-section of firms; we have shown earlier in Figure 5 that supplier capital investment rates are much more dispersed as compared with physical capital investment rates (0.38 and 0.08, respectively). We assume that the entire wage bill needs to be paid in advance and, thus, set $\eta = 1$.

Parameters $p^{shock}$ and $\bar{\zeta}$ govern the occurrence of supply chain disruptions at the steady-state of the model. We use the average disruption rate in the data (0.22) and variance of disruptions (0.01) to simultaneously set $p^{shock} = 0.83$ and $\bar{\zeta} = 0.74$.[10] Figure C4 in Appendix

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

Table 6: Parameter Values

| Parameter | Description | Value | Target/Source | Data | Model |
|---|---|---|---|---|---|
| $\beta$ | Discount factor | 0.99 | | | |
| $\theta$ | Physical capital share | 0.35 | See text | | |
| $\phi$ | Supplier capital share | 0.08 | See text | | |
| $\kappa$ | Returns to scale | 0.85 | | | |
| $\rho_z$ | Persistence of idiosyncratic AR(1) | 0.90 | | | |
| $\sigma_z$ | Std of idiosyncratic AR(1) | 0.10 | | | |
| $\varphi_K$ | Quadratic adj. cost ($k$) | 0.20 | $\sigma[\Delta \log k]$ | 0.08 | 0.07 |
| $\varphi_M$ | Quadratic adj. cost ($m$) | 0.15 | $\sigma[\Delta \log m]$ | 0.38 | 0.22 |
| $\delta$ | Depreciation ($k$) | 0.01 | $\mathbb{E}[\Delta \log k]$ | 0.01 | 0.01 |
| $\eta$ | Fraction of wagebill paid in advance | 1 | | | |
| $p^{shock}$ | Probability of disruption shock | 0.83 | See text | | |
| $\bar{\zeta}$ | Average share of surviving s. capital | 0.74 | See text | | |

reports the distribution of disruption rates in the data.

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

$$\log y_{it} = \beta_0 \log k_{it} + \beta_1 \log m_{it} + \beta_2 \log n_{it} + \lambda \mathbf{X}_{it} + \varepsilon_{it}, \tag{19}$$

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

Table C2 in Appendix reports OLS estimates of Equation (19). We find that the elasticity of sales with respect to supplier capital is statistically significant at the 1 percent level across all columns, and is approximately 0.08 in our preferred specification with a full set of fixed effects (column (4)). This value is reasonable provided that intermediate inputs account for about 70 percent of the output, and the foreign share of intermediate inputs is about 10 percent. In our quantitative implementation, we proportionately re-scale the obtained estimates such that they are consistent with the returns to scale parameter $\kappa$. We summarize all the parameter values that we discussed above in Table 6.

# 5 Quantitative Results

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

## 5.1 Cross-Sectional Implications

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

$$y_{it} = \beta_0 \text{Index}_{it} + \beta_1 \text{Index}_{it} \times \text{FC}_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{20}$$

where the coefficients of interest, $\beta_0$ and $\beta_1$, measure how the outcome variable responds to supply chain disruptions at time $t$, and how this effect varies with the financial position of the firm. The vector of controls, $\mathbf{X}_{it-1}$, includes an intercept, firm and time fixed effects, lagged (logarithms of) physical and supplier capital, lagged productivity, and a lagged measure of a financial constraint.

In order to be consistent with our empirical analysis in Section 3, we need model counterparts for $\text{Index}_{it}$ and $\Delta\text{Index}_{it}$. First, in the model, the supply chain disruption shock $1-\zeta_{it}$ serves as an analog to the empirical object $\Delta\text{Index}_{it}$, since it represents an exogenous shock to supplier capital of firm $i$ at time $t$.

Second, we construct a model-based $\text{Index}_{it}$. We start by regressing $\Delta_t^{t+1} \log m$ on eight lags of $1-\zeta_{it}$. The eight-quarter window is consistent with our empirical analysis, whereby an established trade pair was required to be active at least once over the preceding 24 months, or eight quarters, in order to be considered established in a given time period. The estimated coefficients display a decay pattern, such that the coefficient for lag $t-1$ is a $\sigma$ fraction of the coefficient for the period $t$.

Table 7: Cross-Sectional Implications of Supply Chain Disruptions: Model-simulated Data

| | Returns | | Revenue | | $\Delta \log m$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ΔIndex | -0.008 | -0.003 | -2.246 | 0.121 | | |
| ΔIndex x FC | | -0.002 | | -0.788 | | |
| Index | | | | | 0.444 | 0.505 |
| Index x FC | | | | | | -0.021 |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.057 | 0.057 | 0.822 | 0.824 | 0.221 | 0.222 |

*Notes:* Table 7 reports OLS estimates of Equation (20). The dependent variable is a stock return (columns (1) and (2)), revenue (columns (3) and (4)) and log change in supplier capital $\Delta \log m_{it+1}$ (columns (5) and (6)). ΔIndex is a fraction of supplier capital got destroyed for firm $i$ at time $t$; $\text{Index}_{it}$ is a model-based measure of supply chain disruptions, see text for details. $\text{FC}_{it}$ is a measure of financial constraints (ratio of borrowed funds within the period to capital stock). The vector of controls, $\mathbf{X}_{it-1}$, includes an intercept, firm and time fixed effects, lagged (logarithms of) physical and supplier capital, lagged productivity, and a lagged ratio of borrowed funds to capital.

Our model-based index measure is then defined as $\text{Index}_{it} = \sum_{j=0}^{8} \sigma^j (1 - \zeta_{it-j})$. By construction, this measure increases when a firm experiences a supply chain disruption at time $t$; at the same time, it gradually converges to zero in the absence of disruptions over the preceding eight quarters.

**Measure of Financial Constraints.** In the model simulated data, we measure financial constraint as the ratio of borrowed funds to the total capital stock, $\text{FC}_{it} = \frac{\eta W_t n_{it}}{k_{it}+m_{it}}$. In the model, $\text{FC}_{it}$ is positively associated with productivity and negatively correlated with capital stocks. In other words, capital-poor firms with high productivity tend to be more constrained, as they seek to increase investment to better align their capital stocks with their productivity levels. In line with our empirical analysis in Section 3, we categorize $\text{FC}_{it}$ into five bins and use bin numbers as a measure of financial constraints with higher bin numbers indicating more constrained firms.

We consider stock returns, firm revenue and investment in supplier capital as dependent variables.[11] Table 7 provides the results. Columns (1) and (2) report results for stock

[11] We measure investment in capital as the log difference, which is consistent with how we measured these

returns, or $r_{it}$. We find that, when there is a supply chain disruption shock, firms' returns tend to decline, consistent with our empirical results reported in Section 3. The effect is heterogeneous in the cross-section, with stock returns declining stronger for firms that are more financially constrained.

The next two columns (columns (3) and (4)) demonstrate that supply chain disruption shocks are associated with a negative revenue response, and the response of more constrained firms is stronger. Finally, columns (5) and (6) show that investment in supplier capital, $\Delta \log m$, increases in response to supply chain disruption shocks, as firms attempt to restore their supplier capital stock. We illustrate this point further in Section 5.2, where we analyze the aggregate impact of supply chain disruption shocks.

The interaction term in column (6) indicates that more constrained firms experience a weaker increase in supplier capital investment following a supply chain disruption shock. This finding is consistent with the cross-sectional evidence reported in Table 5. Overall, we conclude that the model captures the central cross-sectional patterns reported in the empirical part of the paper well.

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

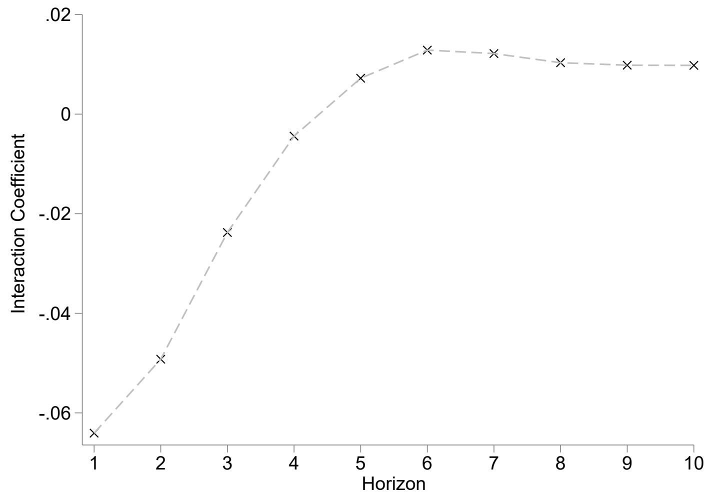
$$\Delta_{t-1}^{t+k} \log m_{it} = \beta_0^k \text{Index}_{it} + \beta_1^k \text{Index}_{it} \times \text{FC}_{it-1} + \lambda \mathbf{X}_{it-1} + \varepsilon_{it}, \tag{21}$$

where the horizon $k \in \{1, \ldots, 10\}$. The vector of controls is the same as in Equation (20).

In the aftermath of a supply chain disruption shock, firms restore supplier capital through investment, and $\{\widehat{\beta_0^k}\}_{k=1}^{10}$ converges to zero as $k$ increases. However, more financially constrained firms recover more slowly, as evidenced by the negative interaction terms for the first several periods as shown in Figure 6. The difference in supplier capital stocks (relative to pre-disruption levels) between constrained and unconstrained firms becomes insignificant

objects in the data (see Section 3). Stock returns are computed as $r_{it} = \frac{Div_{it} + v(k_{it+1}, m_{it+1}, z_{it+1})}{v(k_{it}, m_{it}, z_{it})}$.

Figure 6: Financial Constraint Delays Recovery of Supplier Capital




*Notes:* Figure 6 reports OLS estimates of the interaction term in Equation (21), $\{\widehat{\beta_1^k}\}_{k=1}^{10}$.

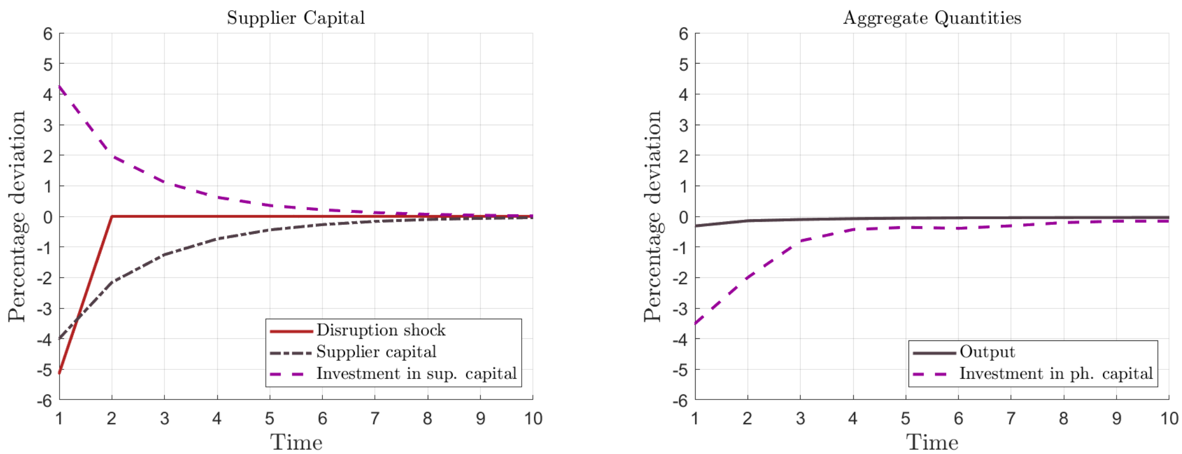
only four to five quarters after the shock. We interpret this as evidence of a persistent effect of financial constraints on firms' recovery from supply chain disruptions.

## 5.2 Aggregate Impact of Disruption Shock

Next, We use our framework to analyze the aggregate impact of a supply chain disruption shock. We consider a perfect foresight (with respect to the aggregate shock $\zeta_t$) transition dynamics whereby firms unexpectedly receive a one-period-long increase in the severity of supply chain disruptions. Specifically, we assume that the economy is in 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 five percent for those firms which receive the disruption shock at $t = 1$; this accords well with three percentage point increase in the share of established trade pairs being disrupted over the last several years as reported in Figure 3. We trace the transition of the economy back to the steady-state in the aftermath of the supply chain disruption shock. Computational details of this exercise are relegated to Appendix B.3.

Figure 7 reports the results. The left panel shows the dynamics of aggregate supplier

FIGURE 7: IMPACT OF SUPPLY CHAIN DISRUPTION SHOCK




(A) Supplier capital (B) Aggregate quantities

*Notes:* Figure 7 reports results for the perfect foresight transition dynamics exercise as described in Section 5.2. Time $t = 0$ corresponds to the steady-state, and firms learn a sequence of shocks $\{\zeta_t\}_{t=1}^{T}$ at $t = 1$.

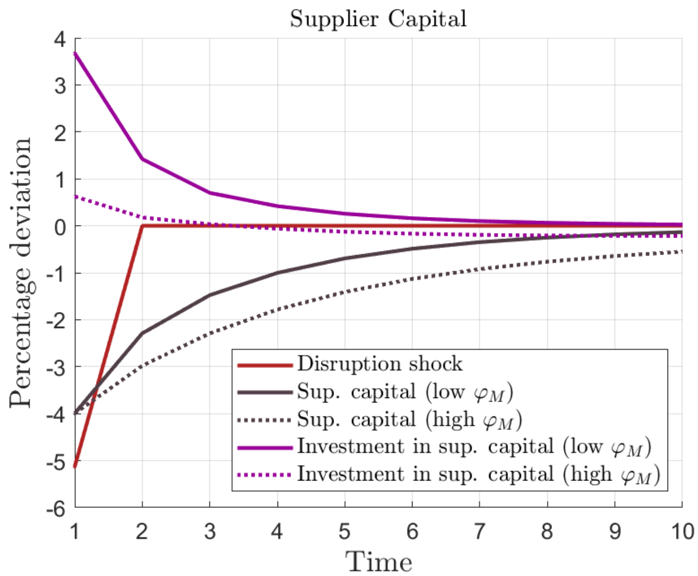
capital. Upon impact at $t = 1$, aggregate supplier capital declines by four percent relative to the steady-state; at the same time, firms start actively investing into supplier capital, as reflected by a four percent increase in aggregate investment $i_m$. It takes the economy about ten quarters to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

The right panel demonstrates that the 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.

## 5.3 Investment in Supplier Capital as an Endogenous Margin of Adjustment

Firms in our model, upon receiving a supply chain 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 the adjustment cost $\varphi_M \to \infty$, the scarring effect of disruptions becomes permanent, as firms are unable to increase their capital stocks.

FIGURE 8: IMPACT OF SUPPLY CHAIN DISRUPTION SHOCK: ROLE OF ADJUSTMENT COSTS




*Notes:* Figure 8 reports results for the perfect foresight transition dynamics exercise as described in Section 5.2. Time $t = 0$ corresponds to the steady-state, and firms learn a sequence of shocks $\{\zeta_t\}_{t=1}^{T}$ at $t = 1$. Solid lines correspond to the parameterized value of $\varphi_M$, dotted lines correspond to the model with a tenfold larger value of $\varphi_M$.

We now demonstrate quantitatively that firms' ability to adjust to supply chain disruption shocks plays a key role in the aggregate dynamics of the model, as higher costs can substantially delay recovery. To illustrate this, we increase the parameter $\varphi_M$ from 0.15 to 3 and repeat the transition dynamics exercise described above. Figure 8 compares the dynamics of aggregate supplier capital and investment in supplier capital along the transition path for the two values of $\varphi_M$. 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 chain disruptions in the aggregate.

# 6 Conclusion

In this paper, we make three contributions. First, using detailed shipment-level data on the universe of U.S. seaborne imports, we document key facts about supply chain disruptions, supplier capital, and firm financial constraints. Second, we develop a general equilibrium model featuring supply chain disruptions and financial constraints, in which heterogeneous firms invest in both physical and supplier capital stocks. The model accounts for the cross-sectional patterns observed in the data. We use the model to demonstrate that firms' ability to accumulate supplier capital through costly investment represents an important endogenous margin of adjustment following supply chain disruptions. Third, we show that financially constrained firms in the model recover more slowly in the aftermath of supply chain disruptions, consistent with our empirical findings.

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# Online Appendix

"Supply Chain Disruptions, Supplier Capital, and Financial Constraints"

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

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# Appendix A: Empirical Appendix

## A.1 Measuring Supplier Concentration and Relationship Strength

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

| | $\Delta_t^{t+1} \log m$ | | $\Delta_t^{t+4} \log m$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Index | 0.1972* | 0.1744 | 0.5954** | 0.3981 |
| | (0.105) | (0.108) | (0.275) | (0.274) |
| Index x FC | | -0.0343*** | | -0.1590*** |
| | | (0.012) | | (0.044) |
| FC | | -0.0099** | | -0.0527*** |
| | | (0.005) | | (0.018) |
| IV | Y | Y | Y | Y |
| F-stat | 19.9 | 18.4 | 29.3 | 27.7 |
| F(index x FC) | | 162.6 | | 177.2 |
| Year-Quarter FE | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| $N$ | 32554 | 31372 | 29828 | 28764 |

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

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

Table A1 reports the results of the IV estimation. According to column (1), the effect of disruptions on investment in supplier capital accumulation is positive and statistically significant at the 10 percent level. The point estimate suggests that a one-standard-deviation increase in the index is associated with approximately a 0.2 percentage point (pp) increase in the investment rate, $\Delta \log m_{it+1}$. Column (2) reveals substantial heterogeneity in responsiveness to supply chain disruption shocks across firms. The interaction term with firm leverage is negative and statistically significant at the 1 percent level, suggesting that the positive average effect reported in column (1) masks a significantly weaker response from leveraged firms. Columns (3) and (4) demonstrate that the patterns become quantitatively more pronounced as the horizon increases. This finding aligns well with the results in Tables 4 and 5 from the main text. We interpret this as evidence of the dynamic nature of investment

TABLE A2: SUPPLY CHAIN DISRUPTIONS AND FIRM INVESTMENT IN PHYSICAL CAPITAL

| | $\Delta_t^{t+1} \log k$ | | | $\Delta_t^{t+2} \log k$ | | | $\Delta_t^{t+4} \log k$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Index | 1.12* | 0.97 | -0.06 | -0.53** | -0.54** | -0.56*** | -0.61*** | -0.62** | -0.65** |
| | (0.62) | (0.63) | (0.08) | (0.21) | (0.21) | (0.21) | (0.30) | (0.30) | (0.29) |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | N | N | Y | N | N | Y | N | N | Y |
| $R^2$ | 0.02 | 0.02 | 0.24 | 0.23 | 0.23 | 0.24 | 0.35 | 0.35 | 0.36 |
| $N$ | 21,497 | 21,497 | 21,497 | 21,453 | 21,453 | 21,453 | 20,802 | 20,802 | 20,802 |

*Notes:* Table A2 reports OLS estimates. The dependent variable is investment rate into physical capital $\Delta_t^{t+j} \log k$ where $j \in \{1, 2, 4\}$. *Index* is a (standardized) firm-level index of supply chain disruptions constructed in Section 2.3. The vector of controls includes year-quarter and firm fixed effects, a standardized, lagged measure of supplier concentration and a standardized, lagged measure of relationship strength. Standard errors are clustered at the firm level. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

decisions and the persistent role of financial conditions in shaping future investment choices.

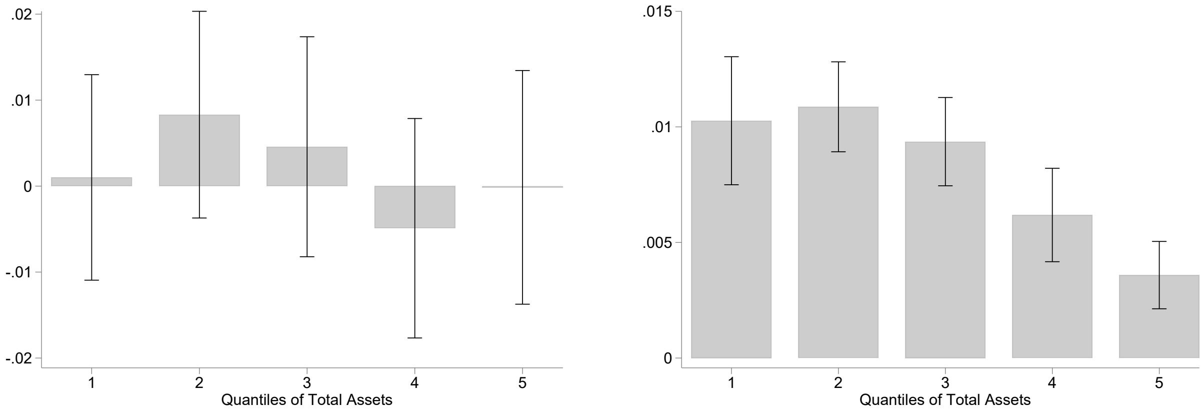
## A.3 Additional Empirical Results

**Supply Chain Disruptions and Investment into Physical Capital** Table A2 reports results for investment in physical capital. The coefficient on the supply chain disruption index is negative once we include the full set of controls, and is statistically significant at the 5 percent level over longer horizons (columns (4)-(9)). Quantitatively, the impact of supply chain disruptions on physical capital investment is weaker as compared to investment in supplier capital (Table 4).

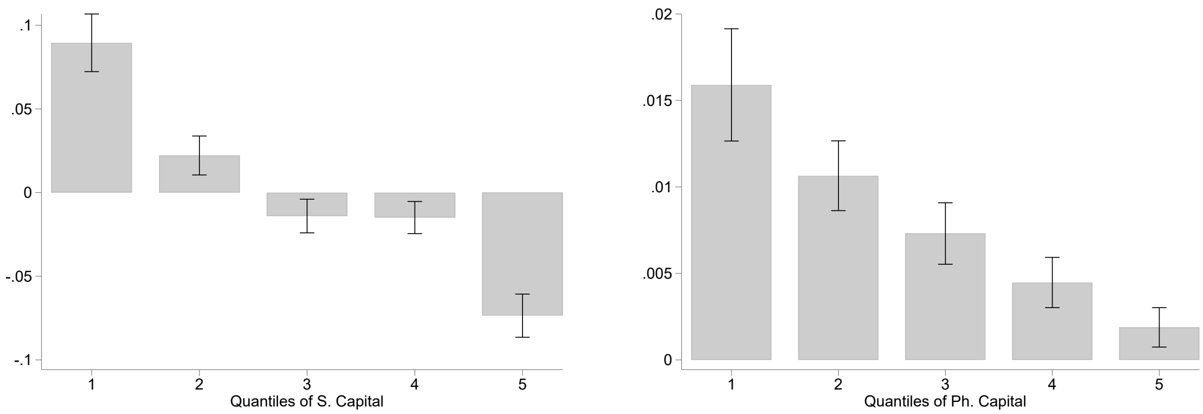
**Firm Size and Investment into Supplier and Physical Capital** Do larger firms invest more in supplier capital? To investigate this, we group observations into five quantiles based on total assets and report the average investment rate in each bin. Panel (A) of Figure A1 shows that there is no strong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

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

Figure A1: Average Investment Rates and Firm Size




(A) Investment in supplier capital by assets (B) Investment in physical capital by assets




(C) Investment in supplier capital by s. capital (D) Investment in physical capital by ph. capital

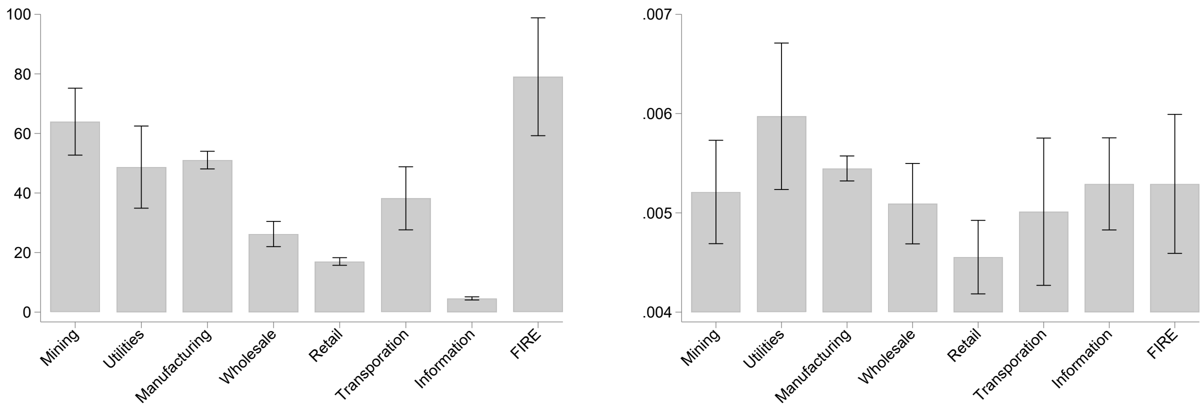
*Notes:* Figure A1 consists of 2 panels. Panel (A) plots the mean investment rate into supplier capital across firm size quantiles (total assets); Panel (B) plots the mean investment rate into physical capital. Vertical intervals represent 95 percent confidence bounds.

20 percent of firms.

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

**Heterogeneity in Supplier Capital and Exposure to Supply Chain Disruptions Across Industries** Panel (A) of Figure A2 shows significant variation in supplier capital across industries. Retail and information firms, on average, have the smallest amount of supplier capital. In contrast, manufacturing, mining, and FIRE firms are at the other end of

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




(A) Supplier capital

(B) Supply chain disruption rate

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

the spectrum, with the largest amount of supplier capital. This finding suggests that firms in different sectors operate differently; for example, while retail and wholesale firms import a significant volume of goods by sea, they tend to work with a large number of suppliers, of which relatively few are considered "permanent" (or established, using our terminology).

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

## A.4 Definitions of Financial Variables

This appendix provides definitions of the financial variables that we constructed using CRSP and Compustat items. The variable names in parentheses correspond to the Compustat item names. The market-to-book ratio, net price margin, and accrual are downloaded directly from the Financial Ratios Suite by WRDS.

– **Stock return** = Logarithm of one plus stock returns;

– **Revenue** = Revenue (`revt`)/Total assets (`at`);

- **Leverage** = (Long-term debt (`dltt`) + Debt in current liabilities (`dlc`))/Total assets (`at`);
- **Cash Flow** = Operating income before depreciation (`oibd`)/Total assets (`at`);
- **Cash** = Cash & short-term investments (`che`)/Total assets (`at`);
- **Long-term debt** = Long-term debt (`dltt`)/Total assets (`at`);
- **Size** = Logarithm of total assets (`at`);
- **Tobin Q** = Market value (`at` + `casho`*`prcc` - `ceq` - `txdb`)/Book value (0.9*`at` + 0.1*`casho`*`prcc`);
- **Dividend** = (Cash dividends on common stock (`cdvc`) + Cash dividends on preferred/preferences Stock (`pdvc`))/Total assets (`at`)
- **Dividend dummy** = **Dividends** > 0;
- **Sales growth** = growth of sales (`revt`) at the firm level;
- **Payout ratio** = (Cash dividends (`dvp+dvc`) + Repurchases (`prstkc`))/Income before extraordinary items (`ib`);
- **Industry sales growth** = growth of median sales (`revt`) at SIC 3-digit level;
- Kaplan and Zingales (1997) **Index** = -1.002***Cash flow** + 0.283***Tobin Q** + 3.319***Long-term debt** - 39.368***Dividend** - 1.315***Cash**;
- Whited and Wu (2006) **Index** = –0.091***Cash flow** + 0.062***Dividend dummy** + 0.021***Long-term debt** – 0.044***Size** + 0.102***Industry sales growth** – 0.035***Sales growth**;

# Appendix B: Model Appendix

## B.1 Definition of Equilibrium

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

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

such that:

1. $H$ solves the household's problem (17)-(18) and $\{C, B, \Xi\}$ are the corresponding policy functions,

2. $\{v, v^{cont}\}$ solve the firm's problem (12)-(16), and $\{n, k', m'\}$ are the corresponding policy functions,

3. labor market clears

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

   where $\mu$ is the stationary distribution of firms across idiosyncratic productivity $z$ and capital stocks $k$ and $m$;

4. bonds market clears (by Walras law):

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

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

5. goods market clears:

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

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

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

6. the distribution of firms $\mu$ is induced by decision rules $k'(k, m, z)$ and $m'(k, m, z)$, and the exogenous evolution of idiosyncratic productivity $z$ (Equation 11);

7. household's decision $\Xi$ is consistent with the stationary distribution of firms $\mu$.

## B.2 Computation Algorithm: Steady-State

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

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

1. guess the equilibrium wage rate, $W$;

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

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

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

### B.2.1 Approximation of Value Functions

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

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

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

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

#### B.2.2 Stationary Distribution

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

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

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

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

which govern the shift of mass along $k$-, $m$-, and $z$-dimensions, respectively. While $\mathbf{Q}_z$ is completely determined by the exogenous stochastic process, matrix $\mathbf{Q}_k$ and matrix $\mathbf{Q}_m$ is constructed so that the model generates an unbiased distribution in terms of aggregates.[12] More precisely, element $(i, j)$ of the transition matrix $\mathbf{Q}_k$ informs which fraction of firms with the current idiosyncratic state $k_i$ will end up having $k_j$ tomorrow. Therefore, this entry of the matrix is computed as:

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

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

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

## B.3 Computation Algorithm: Transition Dynamics

In this section, we outline an algorithm for computing transition dynamics. In the paper, we study the impact of an unexpected shock $\zeta_t$ 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 chain disruption shock $\zeta_t$ will stay at the steady-state level indefinitely;

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

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

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

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

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

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

   Note that we are using value functions scaled by the marginal utility: $\tilde{v}_t = \widehat{MU}_t \times v_t$.

   We also recover the value function $\tilde{v}_{T-1}$ that corresponds to the obtained decision rules. Value function $\tilde{v}_{T-1}$ is then:

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

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

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

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

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

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

# Appendix C: Tables and Figures

Table C1: Key Variables

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

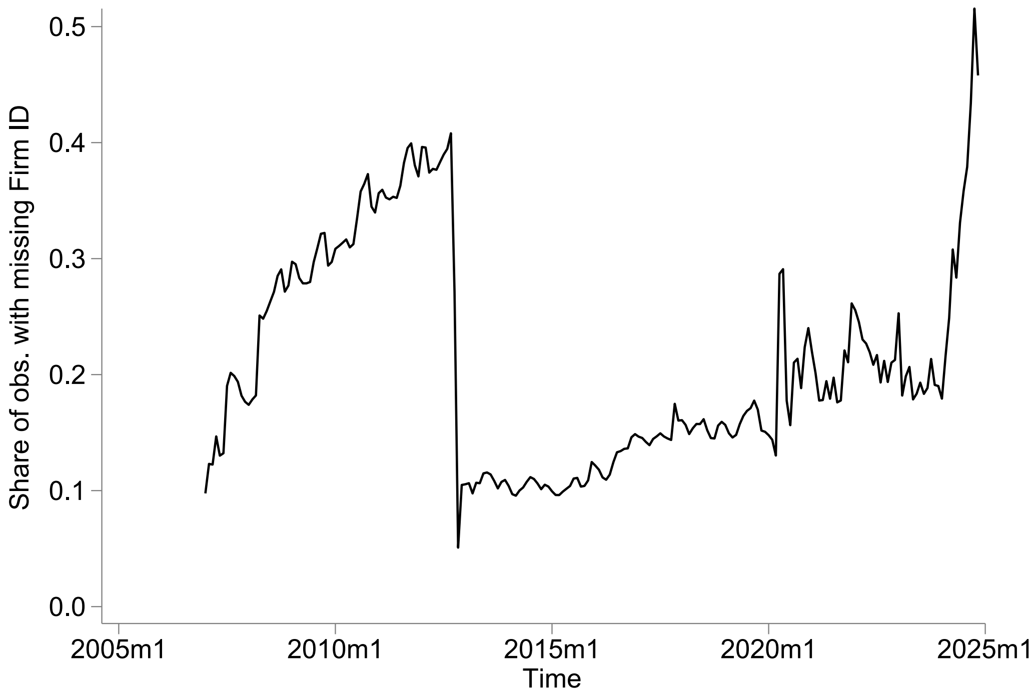
*Notes:* Table C1 provides a list of key variables in S&P Panjiva data.

Table C2: Production Function Estimates

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

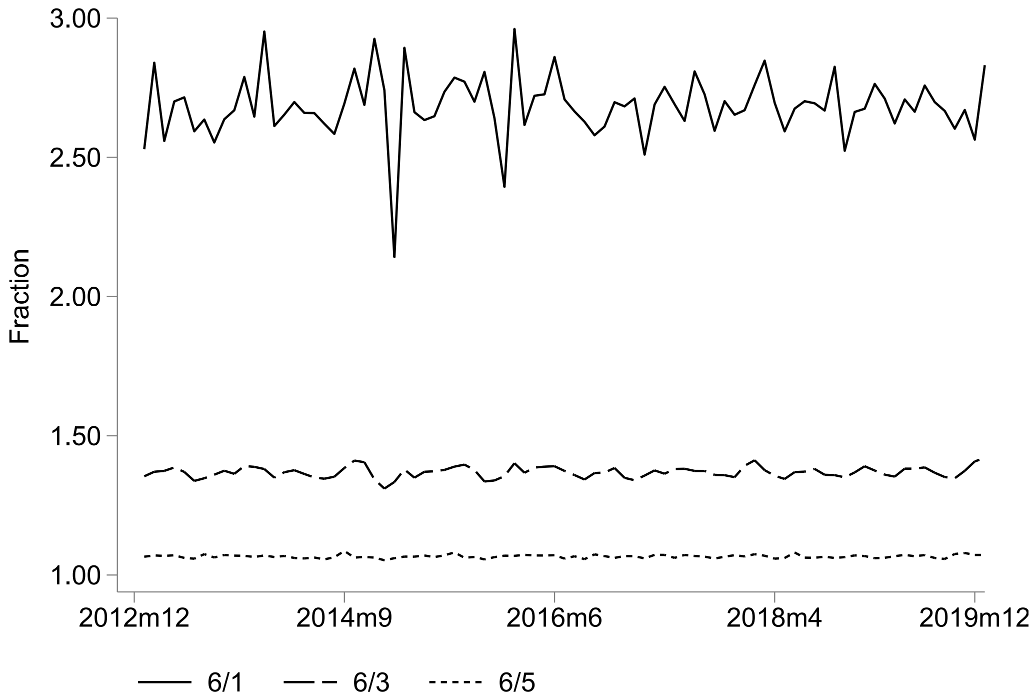
*Notes:* Table C2 reports OLS estimates of the following equation: $\log y_{it} = \beta_0 \log k_{it} + \beta_1 \log m_{it} + \beta_2 \log n_{it} + \lambda \mathbf{X}_{it} + \varepsilon_{it}$, where the dependent variable $y_{it}$ is sales, $m_{it}$ is supplier capital, $k_{it}$ is physical capital,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

Figure C1: Share of Observations with Missing Firm ID



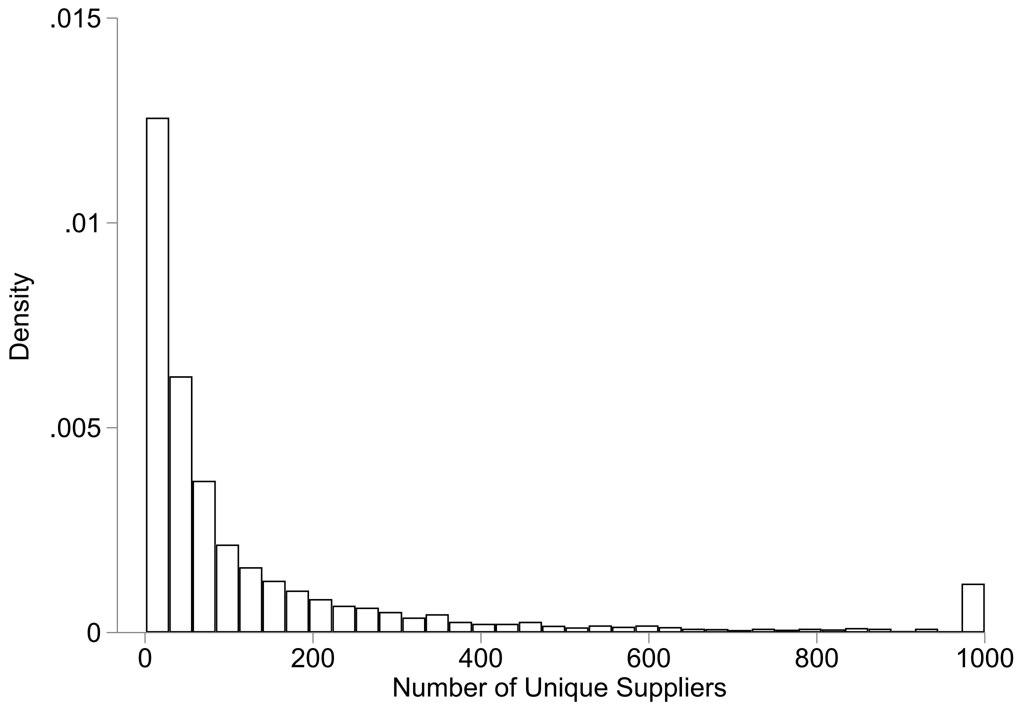

*Notes:* Figure C1 plots the share of observations (per month) with missing `conpanjivaid`.

Figure C2: Illustration of the Imputation Method



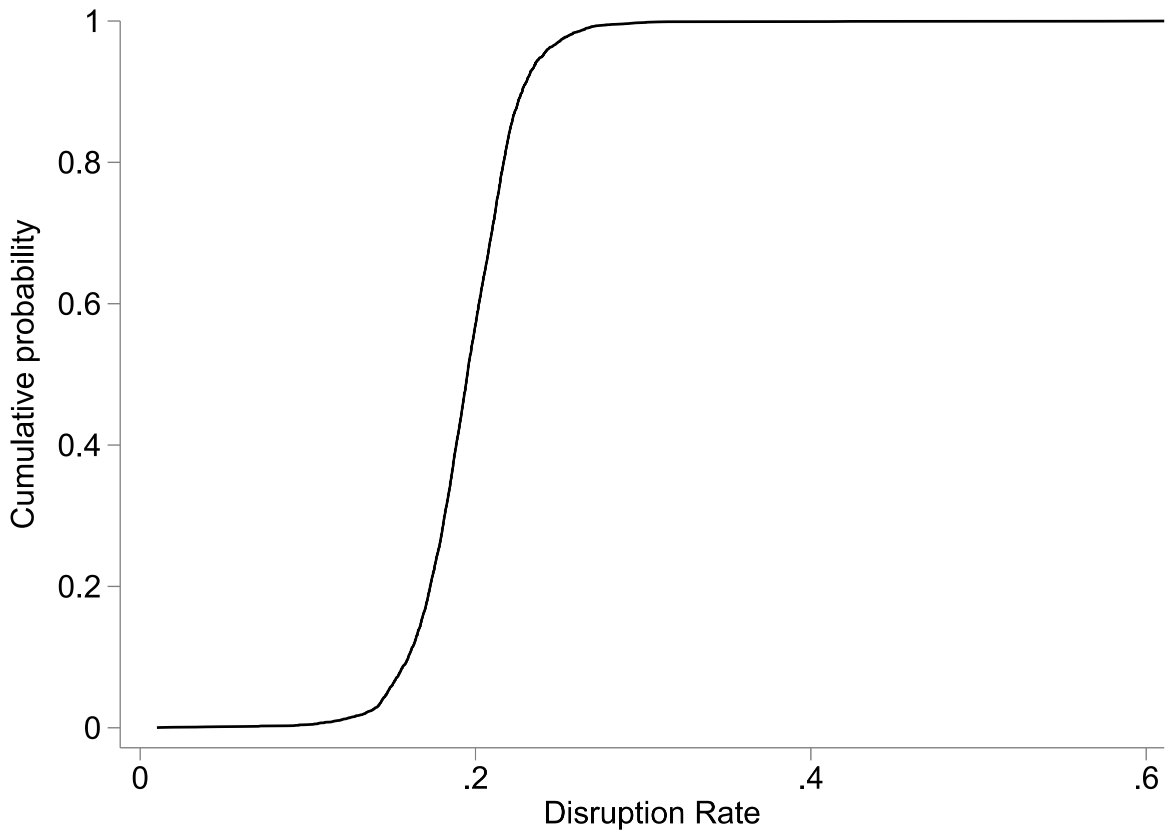

*Notes:* Figure C2 plots 3 lines. The solid line depicts the ratio of established, temporarily inactive trade pairs ($X = 3, p = 12, v = 6$) that recover over the next 6 months and the number of those which will recover next month (6/1). The dashed and dotted lines correspond to ratios 6/3 and 6/5. Time series have been deseasonalized.

Figure C3: Number of Unique Suppliers: Compustat Sample



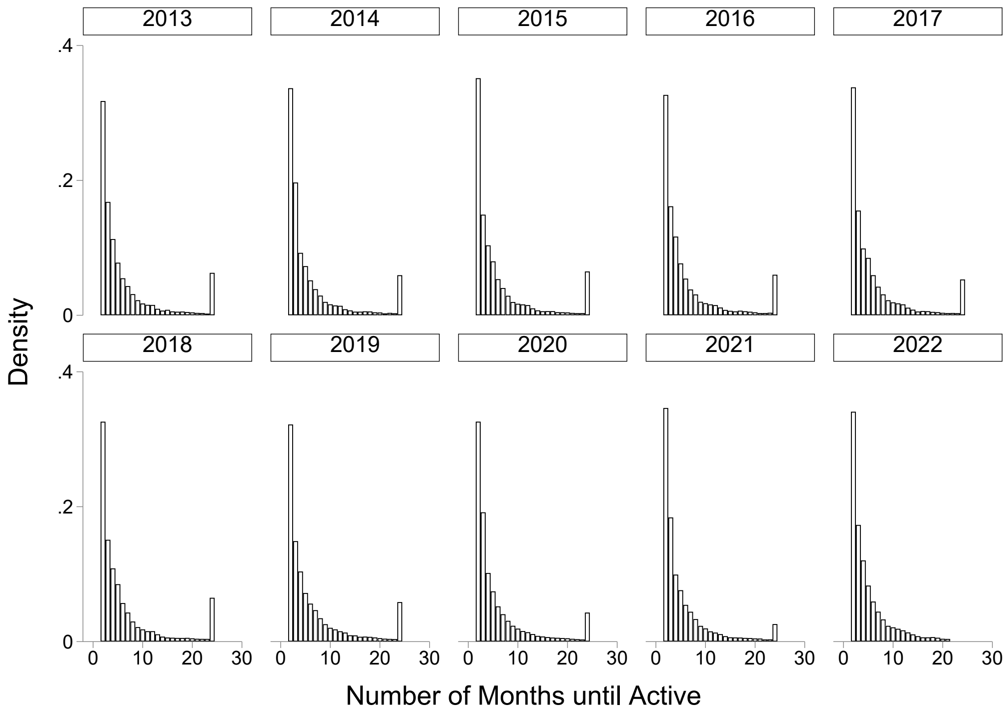

*Notes:* Figure C3 plots distribution of the number of unique suppliers for U.S. public firms (matched to Compustat data). Right tail is truncated at 1000 unique suppliers.

Figure C4: Distributions of Disruption Rates: Pooled




*Notes:* Figure C4 plots the cumulative density function of the disruption rate pooled across products and quarters.

Figure C5: Distribution of Inactivity Spells




*Notes:* Figure C5 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.

## Table C3: Controlling for Intangible Capital

| | (1) Returns | (2) Revenue | (3) $\Delta_t^{t+1} \log m$ | (4) $\Delta_t^{t+2} \log m$ | (5) $\Delta_t^{t+4} \log m$ |
|---|---|---|---|---|---|
| $\Delta$Index | -0.16* | -0.19*** | | | |
| | (0.09) | (0.05) | | | |
| Index | | | 1.40** | 1.74 | 3.23** |
| | | | (0.65) | (1.08) | (1.63) |
| EKP | -0.09*** | 0.07 | 0.38 | 0.54 | 1.00 |
| | (0.03) | (0.05) | (0.37) | (0.71) | (1.18) |
| OK | 0.15 | 10.22*** | 4.03 | 6.66 | 11.18 |
| | (0.37) | (1.04) | (3.96) | (7.26) | (13.05) |
| Time FE | Y | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y |
| $R^2$ | 0.25 | 0.90 | 0.08 | 0.13 | 0.22 |
| $N$ | 170,297 | 52,817 | 21,497 | 21,410 | 20,692 |

*Notes:* Table C3 reports OLS estimates. EKP is the market-to-book ratio accounted for intangible capital from Eisfeldt, Kim and Papanikolaou (2022) and OK is the organizational capital measure from Eisfeldt and Papanikolaou (2013). Controls include the lagged versions of the supplier concentration, relationship strength, logarithm of firm size, net price margin, and accrual. Standard errors are clustered at the firm level. All variables are winsorized at top and bottom 1 percent. *, **, *** denote statistical significance at 10, 5, and 1 percent levels, respectively.