How Do Supply Chain Pressures Affect Monetary Policy Transmission? *

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Abstract

This paper explores how supply chain pressures influence the transmission of monetary policy. I develop a novel firm-level supply chain pressure index using natural language processing techniques applied to earnings call transcripts, and I validate this index at both the sentence and firm levels. Empirically, I find that following an expansionary monetary policy shock, supply chain–pressured firms substitute constrained intermediate inputs with alternatives and increase physical investment more than their unpressured counterparts. Additionally, sectors experiencing high supply chain pressure show a sharper and more persistent price response, with an inflationary overshoot lasting for six quarters. I rationalize these findings using a New Keynesian model with supply chain frictions that reduce the effective inputs available for production and highlight the state-dependent effects of monetary policy.

Keywords: supply chain pressures, investment, inflation, monetary policy, natural language processing, transformer-based language models
Keywords: C63, D22, D24, E22, E30, E52

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1 Introduction

In the aftermath of the COVID-19 pandemic, the global economy has faced unprecedented disruptions to its supply chains. These disruptions have included factory shutdowns, shipping delays, and new challenges stemming from the war in Ukraine and the crisis in the Red Sea. Such events have restricted the flow of essential inputs, limiting production worldwide and resulting in several macroeconomic implications (Acemoglu and Tahbaz-Salehi, 2024). Not surprisingly, supply chain pressures have received significant attention in economic debates, emphasizing the importance of accurately quantifying and monitoring these pressures. A clear understanding of these dynamics is crucial not only for companies directly impacted by the bottlenecks but also for policymakers identifying and managing potential imbalances in the broader economy.

At the same time these disruptions unfolded, central banks adopted accommodative monetary policies to support a swift recovery from the 2020 pandemic-induced recession.[1] While these measures boosted output, they also coincided with a two-year period of high inflation that significantly surpassed the Federal Reserve's average inflation target. This situation posed a challenge to the dual mandate of maintaining price stability while achieving full employment. It also emphasized the need to understand how monetary policy interacts with supply chain pressures. In this environment, supply chain frictions can affect the transmission of these policies and lead to unintended consequences throughout the economy.

In this paper, I examine how pressures in the supply chain affect the transmission of monetary policy to real economic activity and inflation. I begin by creating a new firm-level supply chain pressure indicator using natural language processing techniques, which can be merged with firms' balance sheet data. Next, I empirically analyze how firms respond to expansionary monetary policy shocks when they are supply chain-constrained. I focus on the differences in capital accumulation and price adjustments between firms facing supply chain pressures and those that are not. The empirical findings show that after monetary easing, constrained firms shift spending away from scarce intermediate inputs toward physical capital and raise prices more aggressively than their unconstrained counterparts in response to rising demand.

To rationalize these patterns, I incorporate supply chain pressures into a New Keynesian general equilibrium model by limiting the availability of inputs for production. Penalizing

[1] Note that, the Federal Reserve initiated its first interest rate hike only in March 2022, after supply chain pressures had already peaked in the last quarter of 2021, as indicated by the Global Supply Chain Pressure Index (Benigno et al., 2022) and the measure developed in this paper.

the use inputs when supply chain pressures increase endogenously amplifies capital accumulation after an expansionary shock. Investment becomes a means to satisfy rising demand when inputs are scarce. The model simulations align with the empirical findings and highlight a policy trade-off. Looser policy amid supply bottlenecks fuels short-run inflation; however, it also stimulates long-run capacity expansion that reduces dependence on disrupted inputs.

Supply chain pressures at the firm level are inherently difficult to observe using conventional financial or production data. To address this gap, I exploit the rich textual information found in firms' earnings call transcripts to quantify those pressures. I use transformer-based language models to analyze these transcripts and develop an index that quantifies supply chain pressures at the firm level. My approach involves a two-step model to identify sentences related to these pressures, which significantly outperforms the commonly used "bag-of-words" method. In the first step, I pre-select potentially relevant sentences using dictionary filtering. I construct the dictionary following the iterative process proposed by Grimmer et al. (2022), incorporating natural language processing techniques. In the second step, I fine-tune language models such as BERT, RoBERTa, and FinBERT to identify sentences specifically related to supply chain pressures. I then select the model that achieves the best balance between accurately identifying true positives while minimizing both false positives and false negatives.

Validation of the indicator at the firm level is achieved by benchmarking the index against several well-documented "ground truth" events, such as natural disasters and major logistical failures known to cause supply chain disruptions. Firms directly affected by these events exhibit a clear increase in the supply chain pressure indicator relative to unaffected firms. The events include the Tohoku Earthquake in 2011, Brazil's truck drivers' strike in 2018, and China's COVID-19 shutdown in 2020, for example. At the aggregate level, I calculate the average of the firm-level index across all firms and find it closely tracks established aggregate measures of supply chain disruption in the literature.

Next, I merge the firm-level supply chain pressure indicator with Compustat balance sheet data to assess how monetary policy shocks propagate to real activity and prices in a supply chain-constrained environment. I use local projection regressions (Jordà, 2005) to estimate the dynamic response of firms' capital accumulation to an exogenous monetary policy shock, conditioning the response on each firm's supply chain pressure index. I find that following an expansionary shock, firms facing unusually high supply chain pressure increase their investment by approximately 0.36% three quarters after the shock and by 0.71% nine quarters later, compared to firms not experiencing supply chain pressures.

This finding suggests that firms use capital to produce when input availability is

constrained. An expansionary monetary policy shock boosts aggregate demand, leading firms to increase output. Unconstrained firms can meet this higher demand by using more intermediate inputs, as their delivery can adjust easily. However, when supply chain frictions are significant, the delivery of inputs cannot increase rapidly enough. In these cases, constrained firms must turn to tangible capital to maintain production. In line with this mechanism, firms under high pressure accelerate their investment to overcome input shortages. To further support this substitution channel, I augment this baseline analysis with several complementary exercises.

I first document that following expansionary monetary shocks, firms under supply chain pressure show larger declines in their input-to-capital and input-to-sales ratios, with no change in intangible investment. This highlights a shift toward physical capital rather than a broad increase in overall investment. The pressures are persistent, leading firms to anticipate multi-quarter input shortages and preemptively invest in capital. Analyzing asymmetric policy responses, I find that only expansionary shocks trigger a significant relative rise in physical capital for these constrained firms, indicating that substitution occurs only when constraints bind to meet higher demand. Finally, including interactions between monetary shocks and financial constraint measures does not impact these findings, ruling out credit easing as the primary driver of the observed capital accumulation.

To assess how the inflationary effects of monetary policy vary with supply chain conditions, I estimate differential price responses in sectors experiencing high versus low supply chain pressures.[2] I find that expansionary monetary policy results in higher inflation when supply chain pressures are high. Specifically, price increases in high-pressure sectors exceed those in unconstrained sectors by 1.56% two quarters after the policy shock, and this more inflationary state remains statistically significant for approximately six quarters.

I rationalize these findings using a New Keynesian general-equilibrium model in which a representative wholesale firm invests in physical capital and sources intermediate inputs from upstream suppliers. When supply chain pressures intensify, not all ordered inputs arrive on time or in usable condition (for example, some shipments may spoil during delays). The firm, therefore, combines capital with these "effective" intermediate inputs to produce output. As bottlenecks tighten, the elasticity of ordered inputs with respect to output prices declines, leading wholesalers to increasingly rely on physical capital to meet rising demand.

The model delivers two key predictions. First, when bottlenecks are severe, an expansionary monetary shock amplifies inflation for six quarters. Second, the same shock induces firms to accumulate more capital as inputs become scarce. The gap in capital

[2]Section 4.2 explains why sector-level price data is preferable to firm-level measures in this context.

accumulation between the constrained and frictionless economies peaks in the fourth quarter and remains elevated over a five-year horizon, signaling a sustained expansion of productive capacity. Meanwhile, the inflation differential follows a hump-shaped path, reaching its maximum two quarters after the shock before receding by the end of the sixth quarter. Thus, accommodating monetary policy amid supply chain pressures "crowds in" capital but temporarily intensifies inflation, capturing the state-dependent dynamics observed empirically.

Literature My paper relates to the literature measuring supply chain disruption. Benigno et al. (2022) measured pressures arising at the global supply chain level. Bai et al. (2024) constructed a measure of congestion in ports using satellite data at both global and port levels. Burriel et al. (2023) developed a country-level supply chain bottleneck measure using newspaper. Liu et al. (2023) created a Supply Disruption Index (SDI) using shipment-level transactions to capture supply disruptions in U.S. importing firms. My firm-level supply chain pressure index (henceforth, FSCP) applies natural language processing (NLP) to analyze earnings call transcripts, capturing disruptions faced by all firms. Unlike shipment-based measures, FSCP identifies all supply chain challenges while avoiding the misclassification of demand-driven shipment interruptions.

I contribute to the extensive literature that employs NLP techniques to extract firm-level information for studying economic questions. Recent research has focused on firm-level political and non-political risk (Hassan et al., 2019), exposure to epidemic diseases (Hassan et al., 2023), inflation expectations (Albrizio et al., 2023), inflation risk exposure (Konchitchki and Xie, 2023), supply chain risk (Ersahin et al., 2024), and attention to macroeconomic topics (Song and Stern, 2024). My paper is the first to extract how constrained firms are by supply chain issues from earnings call transcripts.

The macroeconomic literature has quantified the effects of supply chain disruptions, with most studies emphasizing their aggregate implications (Finck and Tillmann, 2022; Alessandria et al., 2023; Bai et al., 2024; Acemoglu and Tahbaz-Salehi, 2024). A related strand of research empirically investigates how monetary policy is transmitted in the presence of supply chain frictions (Laumer and Schaffer, 2025; Balleer and Noeller, 2023). I present the first firm-level evidence that monetary easing during supply chain bottlenecks encourages firms to substitute scarce inputs with capital. This substitution not only expands long-term productivity capacity but also raises short-term inflation.

On the theoretical side, existing models represent supply chain disruptions as exogenous reductions in potential output or negative productivity shocks to analyze optimal monetary policy when frictions are present (Caballero and Simsek, 2023; Fornaro and

Wolf, 2023). Recent research finds that firms operating near full capacity experience larger productivity gains from aggregate demand shocks, such as government spending surges (Ilzetzki, 2024; Fornaro, 2024). I depart from this approach by modeling supply chain pressures as a reduction in input effectiveness rather than total productivity, which endogenously generates higher capital accumulation in the presence of bottlenecks.

Finally, the literature on heterogeneity in the transmission of monetary policy at the firm level establishes that financial conditions significantly impact the investment channel (Ottonello and Winberry, 2020; Jungherr et al., 2022; Jeenas, 2023). My paper demonstrates that supply chain pressures also play an important role in the investment channel.

2 Data

My analysis draws on four principal data sources: (i) earnings-call transcripts from Capital IQ; (ii) firm-level balance-sheet information from the Compustat North America Fundamentals Quarterly database; (iii) high-frequency monetary policy shock measures constructed by Bauer and Swanson (2023); and (iv) sector-level Producer Price Index series published by the U.S. Bureau of Labor Statistics. I describe each of these datasets in greater detail below.

2.1 Earnings Call Transcripts

Publicly listed firms regularly hold earnings conference calls with analysts and other interested parties. During these calls, executives discuss the firm's past and future performance and respond to participants' questions. Most U.S.-listed firms host one earnings call per fiscal quarter, resulting in approximately four observations per firm each year. These calls are usually divided into two sections. They begin with a presentation led by executives such as the CEO or CFO, who describe current conditions and outlook. This is followed by a question-and-answer (Q&A) session with financial analysts and, occasionally, other market participants. I construct a firm-level supply chain pressure indicator using both sections of the call.

I collect 197,265 earnings call transcripts for publicly traded U.S. companies, spanning January 2008 through September 2024, from Capital IQ. Each transcript is provided as a PDF and includes everything that was said during the earnings call. For each, I extract the text, remove unwanted material (e.g., page headers and footers). Finally, I split the cleaned text into sentences for analysis. The first page of each file reports the earnings call date and the company's stock ticker. I use this information to merge the supply chain pressure

indicator with balance sheet data from Compustat Quarterly. For transcripts lacking ticker information, I manually assign the correct ticker by searching for the company's symbol using the firm name extracted from the transcript.[3] Appendix A provides a detailed account of the matching procedure.

2.2 Firms' Balance-Sheet Data

I use the Compustat North America Fundamentals Quarterly database to obtain firm-level balance sheet information. The primary measure of interest is the tangible capital stock, denoted by $k_{i,t}$. I define it as the book value of tangible assets of firm i at the end of period t; this stock is calculated using a perpetual inventory method (see Appendix A.2). The main explanatory variable in analyzing firms' responses to monetary policy shocks is the firm-level supply chain pressure indicator, described and validated in Section 3.

The empirical strategy incorporates several firm-level observables as control variables. To measure a firm's *leverage*, I calculate its total debt (the sum of *dlcq* and *dlttq*) divided by its total assets (*atq*), with both metrics evaluated at book values. I measure a firm's *Size* using the logarithm of its total assets. *Sales growth* is represented as log-differences in sales (*saleq*). *Inventories* are measured as the ratio of *invtq* to total assets. *Cash holdings* are defined as the ratio of cash and short-term investments (*cheq*) to total assets. I use the time since incorporation, sourced from the Compustat database, to proxy for a firm's *age*. Additionally, I compute two separate measures, cost of goods sold (*cogsq*) divided by capital stock, and cost of goods sold (*cogsq*) divided by sales to serve as proxies for the *input-to-capital* and *input-to-sales* ratios, respectively. For the robustness checks, I utilize additional measures of financial constraints, including debt and equity constraints from Linn and Weagley (2024) and the distance to default metric from Ottonello and Winberry (2020).

All nominal variables are deflated using the GDP deflator provided by the Bureau of Economic Analysis, with the exception of PPE, which is adjusted by the investment-specific GDP deflator. I winsorize continuous variables at the 1st and 99th percentiles of their respective distributions. Appendix A.2 offers additional details on data cleaning and sample selection. Following standard practice in corporate finance literature, I use the NAICS 2-digit industry level classification to exclude firms in the utilities sector (code 22), finance, insurance, and real estate (codes 52 and 53), as well as public administration (code 99). The main analysis is focused on firm-quarter observations from 2008Q1 to 2023Q4, as

[3]There are two main reasons why the ticker may not match. First, some transcripts do not include the ticker information in the PDF file. Second, certain companies have changed their ticker symbols.

the FSCP indicator begins in 2008Q1 and the monetary policy shock series concludes in 2023Q4.

2.3 Monetary Policy Shocks

As a measure for assessing monetary policy shocks, I use the U.S. monetary policy shock series proposed by Bauer and Swanson (2023). The raw monetary policy surprises are derived using a high-frequency identification of changes in federal funds futures within short time intervals around FOMC meetings. Subsequently, these surprises are orthogonalized with respect to macroeconomic and financial data identified by Bauer and Swanson (2023) as relevant predictors of interest rate changes surrounding FOMC announcements. Among the various available series of monetary policy shocks, this series is particularly appealing because the orthogonalized surprises eliminate predictable variation, making the measure a clearer indicator of unexpected monetary policy information communicated at each announcement.[4] I then convert the high-frequency shocks into a quarterly frequency through time aggregation.

2.4 Producer Price Index

I obtain monthly Producer Price Index (PPI) data at the 4-digit NAICS industry level from the U.S. Bureau of Labor Statistics. The PPI monitors changes in prices for goods and services during the production stage, prior to reaching consumers. To convert the monthly index to a quarterly frequency, I calculate the simple average of the three monthly observations within each calendar quarter.

3 The Firm-Level Supply Chain Pressure Index

This section introduces the firm-level supply chain pressure index. I begin by defining what supply chain pressures are. Then, I outline the methodology to construct the index, which involves preselecting relevant sentences through a rigorously validated keyword dictionary, fine-tuning transformer-based classifiers, and aggregating the classified data into a firm-level measure. Next, I provide descriptive patterns observed among firms that frequently discuss supply chain disruptions. Finally, I detail the validation exercises conducted at the firm level, using documented "ground truth" events.

[4] In Appendix D.2, I use alternative monetary policy shock series for robustness checks.

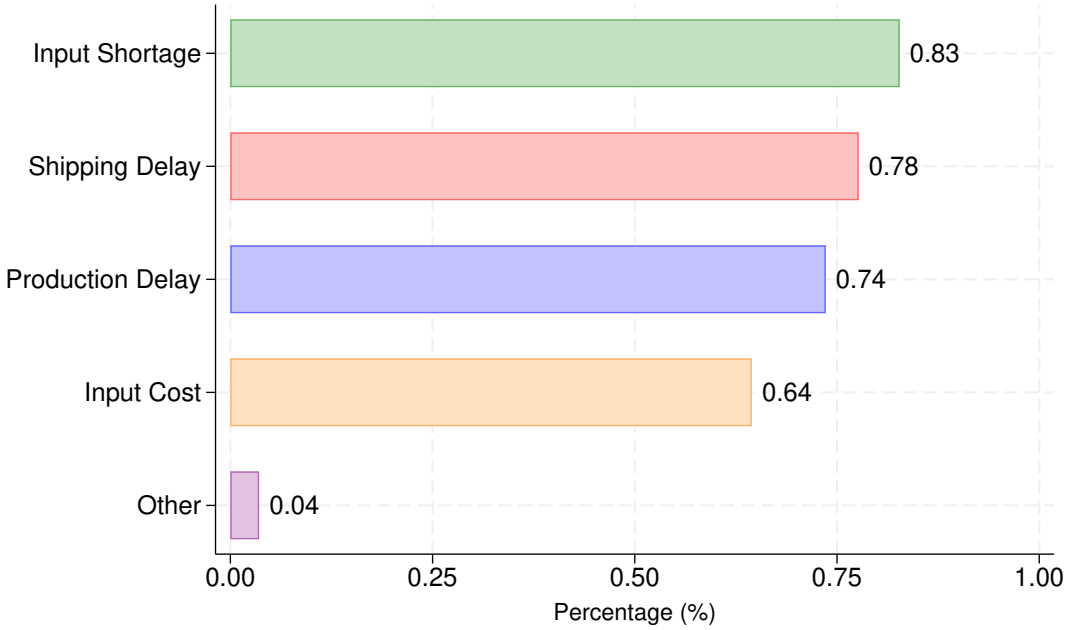


Figure 1: Sources of Supply Chain Pressures

Notes: This figure shows the distribution of supply chain pressures reported by firms in the 2021Q3 special module of the Duke CFO Survey. Among firms that indicated they experienced any supply chain issues, respondents could select one or more of the five pressure types listed on the vertical axis. The horizontal axis displays the percentage of those firms reporting each specific type of issue. The CFO Survey is conducted by Duke University's Fuqua School of Business in partnership with the Federal Reserve Banks of Richmond and Atlanta.

3.1 Defining Supply Chain Pressures

Before constructing the firm-level supply chain pressure indicator, it is important to define supply chain pressures and explain their application in the context of text analysis.

Supply chain pressures arise from several sources (Benigno et al., 2022). Figure 1 shows the four main categories of supply chain challenges that firms reported in the Richmond Fed CFO Survey special module for 2021Q3. Among companies that cited supply chain issues, 83% identified limited material availability as the primary driver.[5] These shortages are often linked to extended delivery times created by logistical bottlenecks such as port congestion, restricted shipping capacity, and other transportation problems. Indeed, 78% of respondents highlighted shipping delays as a key issue. The COVID-19 pandemic magnified these strains: vessels queued at major ports, shipping capacity fell sharply, and freight rates surged (Alessandria et al., 2023; Dunn and Leibovici, 2023).

Logistical bottlenecks and input shortages commonly result in higher material costs;

[5]The CFO Survey, conducted by Duke University's Fuqua School of Business together with the Federal Reserve Banks of Richmond and Atlanta, polls CFOs, VPs of finance, controllers, and other senior financial officers each quarter about their firms' outlook and challenges.

64% of respondents cited rising input prices as a major factor. When suppliers cannot meet demand, production constraints intensify pressures; 74% of surveyed firms reported backlogs caused by material shortages, unplanned factory downtime, or transportation capacity limits. Natural disasters can trigger similar ripple effects because reduced supplier capacity propagates across industries (Barrot and Sauvagnat, 2016; Carvalho et al., 2021). Only 4% of firms pointed to other primary sources of disruption.

In analyzing earnings call transcripts, I use a sentence-level dataset where each entry may or may not contain information about the firm experiencing challenges in its supply chain. Because these sentences are unlabeled, I hand-label a representative subset and extrapolate those labels to the full corpus of transcripts. The definition of supply chain pressure introduced above guides this classification, ensuring that selected sentences reflect adverse shifts in the intermediate input supply curve. In corporate communications, firms describe these pressures using characteristic language, and natural language processing techniques detect such references by mapping text to the pressure dimensions defined earlier.[6]

3.2 Preselecting Relevant Information on Supply Chain Pressures

The dataset is organized at the sentence level, where each sentence serves as a basic observation unit, capturing only a fragment of the firm's overall communication. A key challenge is that only a small percentage of these sentences contain relevant information about supply chain pressures. Without a systematic method to isolate these relevant sentences, reviewing all of them manually would be impossible. To address this challenge, I implemented a dictionary-based filtering step to focus on sentences that may contain important information regarding supply chain pressures. This approach significantly reduces the number of observations to be analyzed.

The dictionary approach allows for filtering sentences that contain specific keywords and phrases related to supply chain issues, such as "supplies" or "supply chain." Panel A in Figure B.1 visually illustrates this preselection process. The large circle represents all the sentences in the dataset, while the medium blue circle inside it indicates the subset of sentences that pass through the dictionary filter. Finally, the small red dots represent the sentences that contain relevant information about supply chain pressures.

Panel B illustrates a scenario where the dictionary is poorly defined. In this situation, important information regarding supply chain pressures may be overlooked if it does not

[6]For example, logistical bottlenecks are described with phrases like "delayed shipments," "port congestion," or "shipping delays." Input shortages are referred to as "lack of materials" or "component shortages." Production constraints may be phrased as "production delays" or "factory shutdowns."

contain the exact keywords from the dictionary. This can lead to a significant number of false negatives, even before fine-tuned language models are applied to identify these sentences. Therefore, the first step in accurately extracting information about supply chain pressures from earnings call transcripts is to create and validate a comprehensive dictionary that encompasses all relevant terms related to supply chain pressure.

To discover relevant keywords for the filtering dictionary, I employed an iterative model proposed by Grimmer et al. (2022). The final dictionary is presented in Table B.1 and detailed in Appendix B.1. To assess the dictionary's effectiveness, I randomly sampled 1,000 sentences from the year 2022, which was the year with the highest level of supply chain pressures in the sample (see Figure C.12). By focusing on this year, the results may underestimate the dictionary's performance, as the high frequency of supply chain pressure-related sentences increases the likelihood of some being missed. Thus, if the dictionary performs well under these conditions, the results would represent a lower bound on its effectiveness.

Among the 1,000 sampled sentences, fifteen are identified as related to supply chain pressures, and one is classified as related to supply chain pressures without containing any dictionary terms. This suggests that the probability of a supply chain pressure-related sentence not being captured by the dictionary is extremely low, estimated to be no greater than 0.1% (1 out of 1,000).[7]

3.3 Fine-tuning Language Models

To measure firm-level supply-chain pressures, I fine-tune several Transformer-based language models. Specifically, I assess the performance of BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), and FinBERT (Araci, 2019) in detecting sentences with relevant supply chain content. For comparison, I also include a traditional bag-of-words approach based on a dictionary from Burriel et al. (2023), which they use to construct a newspaper-based supply chain bottleneck index.

I randomly select 10,000 sentences, each containing at least one dictionary term, and have them human-labeled as either containing relevant information about firm-level supply chain pressures (classified as 1) or not (classified as 0). The dictionary used for filtering and its construction details are provided in Appendix B.1. Each fine-tuned model is trained on this labeled set to estimate the probability that a sentence refers to ongoing

[7] As a robustness check, I use the fine-tuned language model described in Section 3.3 to classify an additional 1,000 random sentences that do not contain any words from the dictionary. The language model understands synonyms and has the ability to identify sentences that discuss similar concepts in different ways. Among these sentences, the model identifies eight as supply chain pressure-related. Out of those, only two truly contain information about supply chain pressures.

Table 1: Out-of-Sample Validation

	Precision	Accuracy	Recall	Specificity	F-1 Score
Bag of Words	74.36%	70.00%	24.37%	95.33%	36.71%
BERT	90.01%	91.80%	86.55%	94.71%	88.28%
roBERTa	92.92%	93.40%	88.23%	96.27%	90.51%
FinBERT	86.54%	90.09%	88.23%	94.38%	87.73%

Notes: This table reports the metrics: precision, accuracy, recall, specificity and F-1 score for all four methods considered. The methods are Bag-of-Words, BERT, RoBERTa, and FinBERT. Appendix C.1 displays additional details on how each metric is calculated.

pressures in a firm's supply chain. The classification is probabilistic, with language models assigning a probability that a sentence relates to supply chain pressures. A sentence is classified as 1 (supply chain pressure-related) if its predicted probability exceeds 0.5.

Hyperparameters are chosen using grid search over three learning rates (1e-5, 2e-5, 5e-5) and three batch sizes (4, 8, 16). I employ early stopping during training if the validation loss fails to improve for two consecutive epochs to prevent overfitting.

3.4 Classifier Performance at Sentence Level

Table 1 compares the three Transformer-based methods described above on an out-of-sample set of 1,000 randomly selected sentences, each containing at least one word from the dictionary in B.1. As a baseline, I also implemented a simple bag-of-words classifier using the "supply" and "bottleneck" dictionaries from Burriel et al. (2023). In their approach, an article is flagged as related to supply chain pressures if it contains at least one term from each dictionary.[8]

All three Transformer models significantly outperformed the bag-of-words baseline, each exceeding 90% accuracy. The fine-tuned RoBERTa model achieved the highest accuracy (93.4%) and F1 score (90.5%), so I adopted it for the remainder of the paper to measure firms' supply chain pressures. Appendix C provides full confusion matrices for all methods and details on how each metric is calculated. Table 2 presents examples with the highest RoBERTa likelihood scores for supply chain pressure, and the model's assigned probability for each.[9]

[8]The supply dictionary includes: *supply chain*, *supply*, and *supplies*. The bottleneck dictionary includes: *bottleneck*, *bottlenecks*, *shortage*, *shortages*, *woe*, *woes*, *disruption*, *disruptions*, *problem*, *problems*, *scarcity*, *scarcities*, *lack*, *delay*, *delays*, *backlog*, and *backlogs*.

[9]Unsurprisingly, the bag-of-words method performed worst overall. Its restrictive nature generated many false negatives (lowering recall and thus the F1 score) and also produced numerous false positives (reducing precision). As a result, this method achieved only 70% accuracy, highlighting its limitations in capturing the supply chain pressure context in earnings calls.

3.5 From Sentences to a Firm-Level Indicator

Not all sentences convey information about supply chain pressures. Many sentences are classified with extreme predicted probabilities close to 0 or 1, indicating clear non-pressure or pressure statements. However, Figure C.1 shows a significant concentration of scores in the intermediate range, which corresponds to ambiguous cases. This distribution supports a probability-weighted approach. I weigh each sentence by its predicted likelihood of being pressure-related, allowing higher confidence classifications (with probabilities near 1) to have a greater influence, while marginal cases (with probabilities around 0.5) are downweighted. Therefore, by leveraging RoBERTa's predicted likelihood scores, I can reduce the impact of borderline misclassifications.

The raw FSCP index at firm i at time t is given by:

$$\text{FSCP}_{it} = \frac{\sum_{s \in Sentences(i,t)} W_s}{\sum \text{Sentences}_{it}}$$

The raw index captures the share of sentences that provide information about firm i's supply chain pressure at time t. Each sentence is weighted by W_s, reflecting the probability that sentence s is related to supply chain pressures.

3.6 Overview of the Raw FSCP Index

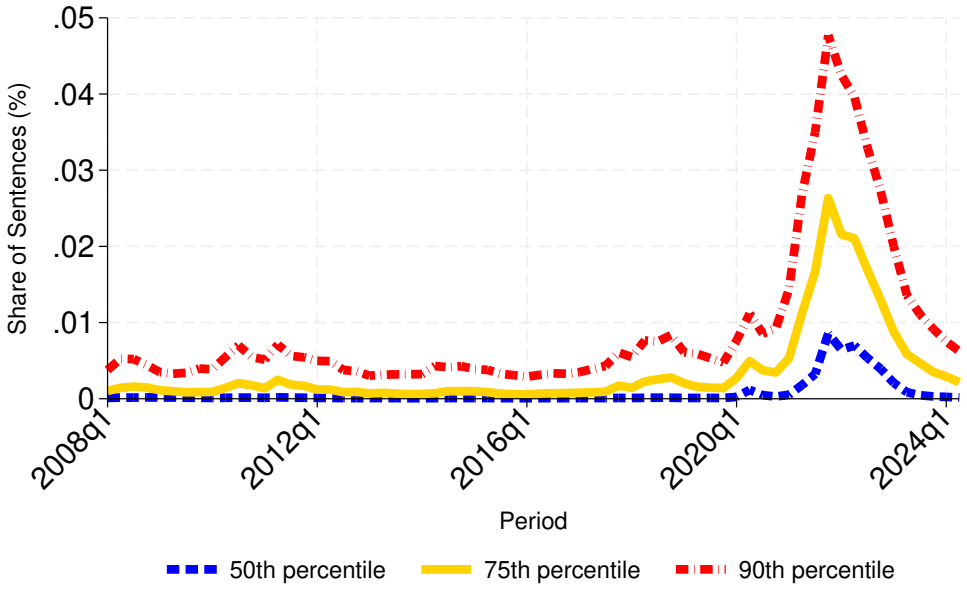
In this subsection, I use the raw FSCP index to establish several key descriptive facts that guide the subsequent analysis. Panel A in Figure 2 plots the quarterly evolution of the 50th, 75th, and 90th percentiles of the indicator. At any given time, at least ten percent of firms report experiencing some level of supply chain pressure, highlighting the consistent prevalence of these disruptions. Second, during the supply chain crisis, more than half of the firms reported supply chain issues, with the intensity of pressure reported by firms in the upper percentiles reaching their highest levels on record.

These aggregate patterns are important on their own, but they conceal substantial variations across different industries and firms. Panel B of Figure 2 compares the median raw FSCP by sector before and after the pandemic. In the period before 2020, median pressure was low across most sectors, but there was positive growth in most sectors. Services and Information reported virtually zero FSCP, reflecting their limited reliance on intermediate inputs. In contrast, between 2020 and 2023, every sector experiences a marked increase in supply chain pressures. Although wholesale trade and manufacturing report the highest absolute median levels, manufacturing, retail trade, and construction see even more significant percentage increases compared to their pre-crisis levels.

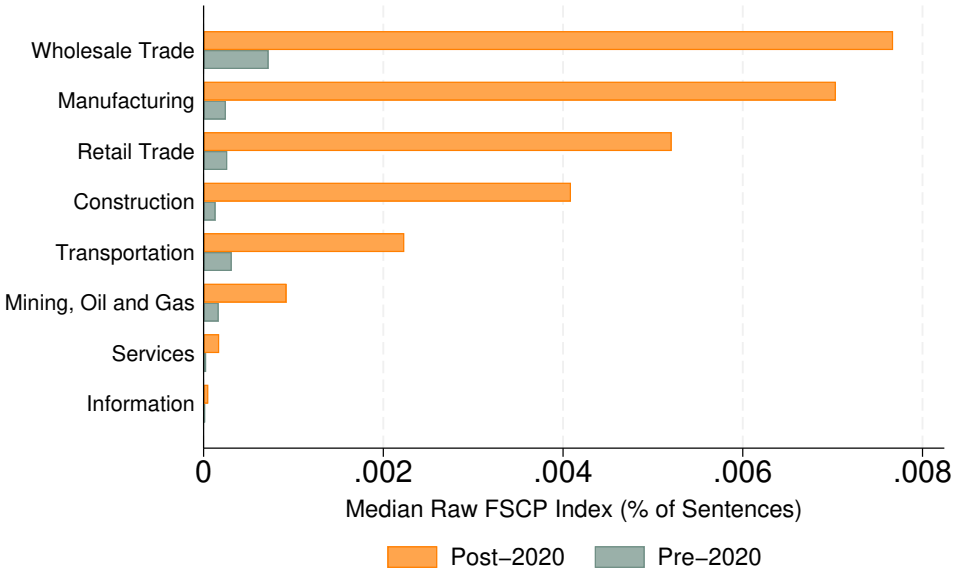
Table 2: Sentences classified by RoBERTa with the highest likelihood score

Firm Name	Date	Sentences	Score
Timberland Co	Nov 04, 2010	However, as I have mentioned earlier, our supply chain is challenged by a number of factors including higher labor, product and transportation cost, which began to impact a result in Q3.	0.9983
Micron Technology Inc	Dec 20, 2012	I think in concert with some knock-on effects that the disruptions created in our overall supply chain really just led to inability to get all the products out.	0.9981
LyondellBasell Industries N.V.	Feb 02, 2016	The specific logistics issue I described, I think that will run its course by the end of Q1.	0.9982
Emerge Energy Services LP	Nov 01, 2017	Our volumes increased by 6%, but are still restricted by logistics bottlenecks.	0.9982
3M Company	Apr 27, 2021	In addition, the expected increase in cost for raw materials and logistics and in some cases, constrained availability.	0.9984
Flowserve Corporation	Feb 24, 2022	We continue to expect and have guided for supply chain, logistics and labor availability to remain challenging in the first half of 2022.	0.9995
Avery Dennison Corporation	Feb 02, 2023	Clearly, there was a lot of supply chain constraints, issues with material and labor.	0.9982

Notes: This table lists sentences classified as related to supply chain pressure by RoBERTa with their associated company name, earnings call date, and the probability score assigned by RoBERTa indicating the likelihood that the sentence pertains to supply chain pressure.



(A) Quarterly Percentiles of the Raw FSCP Index



(B) Supply Chain Pressures Discussions by Sector

Figure 2: Overview of Supply Chain Pressures Discussions

Notes: Panel A illustrates the quarterly trends of the 50th percentile (dashed blue line), 75th percentile (solid yellow line), and 90th percentile (dash-dottted red line) of the raw FSCP index. Panel B presents a comparison of each sector's median raw FSCP from 2008 to 2020 (grey bars) and from 2020 to 2023 (orange bars). The sectors are categorized by two-digit NAICS codes, except for services, which groups together all service industries.

Next, I characterize a "typical" supply chain-pressured firm. I classify firms as systematically pressured if their median raw FSCP over the entire sample exceeds the cross-sectional median All other firms are considered not to be systematically pressured. This classification relies solely on each firm's time series median, so the groupings remain consistent over time. Table C.3 displays the summary statistics for both groups, revealing clear contrasts in balance sheet profiles.

On average, systematically pressured firms are larger (log of total assets: 7.20 vs. 6.42). They are also more capital-intensive (log of tangible capital stock: 5.71 vs. 4.43; capital-to-assets ratio: 0.34 vs. 0.26). This elevated capital intensity suggests that these firms invest in machinery or automation to compensate for scarce inputs during periods of tightened supply chains. In terms of inventories, pressured firms hold three times more (0.15 vs. 0.05 of assets), yet maintain significantly lower cash reserves (0.16 vs. 0.28), indicating a trade-off between operational resilience and liquidity. Their cost-of-goods-sold-to-assets ratio is higher (0.19 vs. 0.12), reflecting increased input costs under pressure. Pressured firms exhibit a higher sales-to-assets ratio (0.28 vs. 0.20). However, leverage and average sales growth remain virtually identical. Finally, the raw FSCP score is roughly six times larger for the pressured group (0.51 vs. 0.08).

3.7 Standardized FSCP

These baseline differences highlight that supply chain pressures are associated with variations in firm and sector structure, which motivates the use of a within-firm standardized indicator. This approach effectively filters out systematic pressures, emphasizing the magnitude of unusual, firm-specific supply chain disruptions. As a result, the findings are not affected by permanent differences in responsiveness among firms.[10]

I standardize the FSCP by subtracting each firm's pre-crisis mean and dividing by its standard deviation over the same period. This normalization measures pressures relative to a firm's typical conditions, preventing extreme shocks during the crisis from distorting firm-level differences and ensuring that the index accurately captures the true supply chain impacts on individual firms. The standardized index has a mean of zero and unit variance, meaning that a value of one corresponds to pressure one standard deviation

[10]Figure C.11 illustrates both the raw and standardized FSCP for Boeing and Walgreens. In the raw FSCP, Boeing consistently shows a higher proportion of supply chain-related sentences, likely due to its complex global network. However, the standardized FSCP indicates that Walgreens experienced more significant peaks of unusual pressures than Boeing in 2022. This highlights the value of the standardized measure in identifying truly abnormal supply chain pressures that could generate different responses from the firms.

above that firm's historical norm.[11]

3.8 Validations

After identifying sentences related to supply chain pressures and aggregating this information at the firm level, I documented key descriptive patterns among firms that frequently discuss supply chain disruptions. In this subsection I validate the FSCP indicator as a reliable measure of firms' supply chain pressures.

A high-performing sentence-level classifier does not guarantee strong performance when aggregating these classifications into higher-level metrics, such as firm-level measures. The model may still produce biased firm-level measures if errors accumulate unevenly across transcripts, resulting in inaccurate indicators.

I focus on validation tasks that closely align with the specific economic concept being measured (Ganguli et al., 2024). The validation exercises concentrate on "ground truth" events, such as natural disasters, which have caused well-documented supply chain challenges for the affected firms. In Appendix C.2, I conduct several exercises that meet these criteria to validate the indicator. Most of the validation employs a difference-in-difference approach, where I identify a group of firms directly exposed to the "ground truth" event (the treatment group). If the index accurately captures supply chain disruptions, firms in the treatment group should exhibit significantly higher short-term pressures compared to those not directly affected by these events (the control group). The exercises in Appendix C.2 confirm the indicator's efficacy in capturing firm-level disruptions.

Appendix C.3 validates the index at the aggregate level by comparing it with traditional aggregate supply chain disruption measures from the literature. The aggregate FSCP is constructed as the quarterly cross-firm average of the firm-level index. It correlates strongly with established disruption measures, with coefficients ranging from 0.72 to 0.91. These high correlations are reassuring, as the series are constructed using different data sources and methodologies yet yield similar results.

4 Monetary Policy Transmission

This section empirically estimates how supply chain frictions affect the transmission of monetary policy through real activity and prices.

[11] Validation results at the firm level in Appendix C.2 are robust to standardizing by the full-sample mean and standard deviation and using the raw FSCP indicator.

4.1 Investment

To investigate the impact of monetary policy under supply chain pressures on real economic activity, I focus on firms' tangible capital. This variable is directly observable at the firm level and can be closely linked to my measure of supply chain pressures. Unlike more volatile indicators such as inventories or sales, tangible capital reflects irreversible investments in assets. This allows for a clearer understanding of how supply chain frictions affect the responses of constrained firms regarding real economic activity

Let $k_{i,t+h}$ denote firm i's tangible capital stock h periods after a monetary policy shock at time t. I estimate a panel local projection approach (Jordà, 2005) in which the dependent variable is the cumulative change in the log of tangible capital, $\Delta_h \log(k_{i,t+h}) \equiv \log(k_{i,t+h}) - \log(k_{i,t-1})$. The main regressor is the monetary policy shock at t interacted with firms' supply chain conditions at the end of period $t-1$, along with a vector of additional controls.

I use the following local projection specification:

$$\begin{aligned}\Delta_h \log(k_{i,t+h}) =& \alpha^h + \beta^h MPS_t \times \mathbb{1}FSCP_{i,t-1} + \theta^h \mathbb{1}FSCP_{i,t-1} + \gamma^h Z_{i,t-1} \\ &+ \eta^h Z_{i,t-1} \times Y_{t-1} + \alpha_i^h + \alpha_{s,t}^h + \epsilon_{i,t}^h.\end{aligned} \tag{4.1}$$

where $k_{i,t+h}$ is the firm-level outcome variable measured in quarter $t+h$ for $h = 0, 1, 2, \ldots, 10$. Here, $\mathbb{1}FSCP_{i,t-1}$ is an indicator variable that equals one if firm i's supply chain pressure at the end of period $t-1$ is above its historical mean. This captures firms facing unusually high supply chain pressures. $Z_{i,t-1}$ is a vector of firm controls that includes one lag of size, leverage, sales growth, cash over assets and inventories over assets. The vector Y_{t-1} contains real GDP growth and interactions with all firm-level variables to control for differences in sensitivities to the business cycle. α_i^h denotes firm fixed effects. Since the main goal is to evaluate differences in firms' responses to monetary shocks conditional on unusual supply chain pressures, I include industry-time fixed effects, $\alpha_{s,t}^h$, to control for all common, time-varying industry-level shocks. This allows the coefficient β^h to reflect only the differential response of pressured versus unconstrained firms. Finally, $\epsilon_{ijc,t+h}^h$ is the error term, which is two-way clustered at the firm and time levels.

Intuitively, an expansionary monetary policy shock raises aggregate demand, encouraging firms to increase output. For unconstrained firms, this adjustment typically occurs through higher utilization of intermediate inputs, as they are fully flexible. However, when supply chain frictions bind, input deliveries cannot rise sufficiently to meet the new demand. As long as capital and intermediate inputs are substitutable in production, constrained firms respond by accelerating investment in tangible capital. In other words,

faced with a shortage of inputs, these firms substitute capital to expand their productive capacity. Consistent with this mechanism, Figure 3 shows that firms under high supply chain pressure invest significantly more in physical capital. The gap is approximately 0.36% three quarters, and 0.71% nine quarters, relative to unconstrained firms following an expansionary monetary shock. To further validate this substitution channel, I conduct several additional empirical exercises.

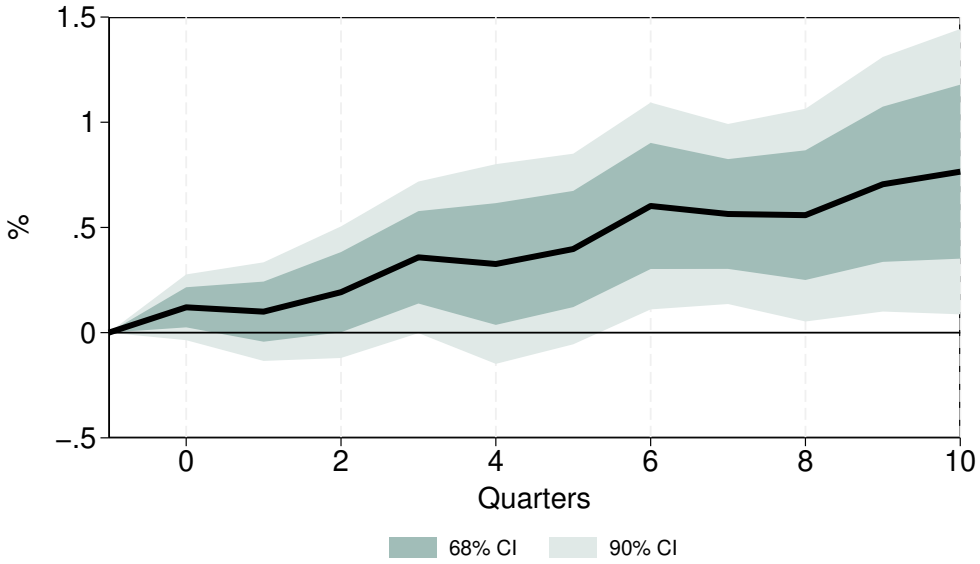


Figure 3: The Effect of Monetary Policy on Firms' Investments: Supply Chain-Pressured vs. Non-Pressured.

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in tangible capital investment in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on sectors experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in the outcome variable.

Changes in Input-to-Capital and Input-to-Sales Ratios: To provide direct balance-sheet evidence of input–capital substitution, I rerun the local projections in Equation 4.1 using the log changes in the cost of goods sold-to-capital ratio and the cost of goods sold-to-sales ratio. Figure D.1 presents estimates of the interaction coefficient β^h on $MPS_t \times \mathbb{1}FSCP_{i,t-1}$. Following an expansionary shock, firms under supply chain pressure exhibit a decline in both ratios relative to unconstrained firms. This drop in input intensity supports the view that constrained firms divert spending away from intermediate inputs toward tangible capital, consistent with the substitution channel uncovered in the investment results.

No effect on intangible investment: I replicate the baseline local projections using intangible capital investment as the dependent variable. Figure D.2 displays the β^h estimates for the interaction $MPS_t \times \mathbb{1}FSCP_{i,t-1}$ at each horizon. Consistent with the hypothesis that only tangible investment can substitute for constrained inputs to meet higher demand, I find no statistically significant differential effect on intangible investment. This null result strengthens the idea that the investment response among supply chain-pressured firms reflects a substitution channel into physical capital rather than a generalized increase in all forms of investment.

Asymmetric investment responses to monetary shocks: I explore the asymmetric effects of expansionary and contractionary monetary policy shocks because firms' responses should differ if they substitute inputs with capital. After an expansionary shock, supply chain-pressured firms cannot simply buy more inputs and must instead invest in capital to expand capacity and meet higher demand. In contrast, unconstrained firms can respond to the increased demand simply by buying more inputs without requiring extra investment. Under a contractionary shock, both constrained and unconstrained firms can reduce input purchases to adjust to declining demand. As a result, there is less differentiation in their investment responses.

I extend specification 4.1 to:

$$\begin{aligned}\Delta_h \log(k_{i,t+h}) =& \alpha^h + \beta^h_{exp} MPS^{Exp}_t \times \mathbb{1}FSCP_{i,t-1} + \beta^h_{con} MPS^{Con}_t \times \mathbb{1}FSCP_{i,t-1} \\ &+ \theta^h \mathbb{1}FSCP_{i,t-1} + \gamma^h Z_{i,t-1} + \eta^h Z_{i,t-1} \times Y_{t-1} + \alpha^h_i + \alpha^h_{s,t} + \epsilon^h_{i,t},\end{aligned} \tag{4.2}$$

this equation differentiates between expansionary (MPS^{Exp}_t) and contractionary (MPS^{Con}_t) monetary policy shocks. This distinction enables the testing of asymmetric responses in firms' investment dynamics to these two types of shocks.

The main coefficients of interest are β^h_{exp} and β^h_{con}. The coefficient β^h_{exp} captures the effect of an expansionary monetary policy shock on investment for firms facing unusual supply chain pressures. It indicates whether these constrained firms increase their investment more or less than non-constrained firms after the shock. Conversely, β^h_{con} measures the impact of a contractionary monetary policy shock. This coefficient allows us to estimate whether firms constrained by supply chains reduce their investment differently than those that are not under tightening conditions. Together, these coefficients help determine if firms respond differently to expansionary and contractionary monetary policy under unusual supply chain pressures.

Panel A in Figure D.3 shows that constrained firms substantially increase physical capital investment after expansionary shocks. These firms exhibit an additional increase of 1.9% in physical capital investment three quarters after the shock and 2.2% nine quarters after the expansionary shock. By contrast, Panel B shows no significant differential effect under contractionary shocks, reinforcing the substitution channel from inputs to capital.

Pressure persistence: A natural concern is that, if supply chain pressures dissipate quickly, tangible investments may not pay off due to the time required to build. Table D.1 reports first-order Markov transition probabilities for firms moving from $FSCP_{i,t} = 1$ to $FSCP_{i,t+1} = 0$. Firms remain unusually pressured ($FSCP = 1$) in the next quarter with a probability of 60.36% . This high persistence implies that input shortages typically last multiple quarters. As a result, firms have an incentive to invest in physical capital, a durable substitute for constrained intermediate inputs.

The role of financial constraints: An alternative explanation is that firms under high supply chain pressure may also face tighter financing conditions. Thus, an expansionary monetary policy shock could disproportionately alleviate their funding constraints and spur additional investment. To address this possibility, I included interactions in the baseline equation between MPS_t and common measures of financial constraints (such as cash-to-assets (liquidity), distance to default, leverage, age, and both debt and equity constraints from Linn and Weagley (2024)). As shown in Figure D.4, the coefficient on $MPS_t \times \mathbb{1}FSCP_{i,t-1}$ remains virtually unchanged in magnitude and significance. This confirms that financial constraints are unlikely to drive the observed investment responses during periods of supply chain pressure.

Robustness checks: I perform several robustness exercises in Appendix D. First, I restrict the sample from 2008Q1 until 2019Q4 to verify that the results are not driven by the post–COVID–19 surge in supply chain pressures. Second, I test alternative U.S. monetary policy shock series from the literature. Finally, I re-estimate the main specification using various alternative measures of supply chain pressure instead of the binary indicator based on a firm's historical mean.

4.2 Prices

Firm-level prices are unobservable in the Compustat dataset. Consequently, researchers estimate markups using the production approach (Loecker and Warzynski, 2012; De Loecker et al., 2020). This technique recovers a firm's markup by estimating the output elasticity

of a variable input and measuring that input's revenue share. This method relies on the key assumption that the variable input is perfectly flexible. However, supply chain pressures violate the input flexibility assumption. Bond et al. (2021) show if the input used to calculate the markup incurs adjustment costs, then the estimated output elasticity incorporates both the markup and the marginal shadow cost of the constrained input, which may bias markup estimates.

To address these concerns, I use the following specification at the sector level to estimate the impact of monetary policy on prices in the context of supply chain pressures:

$$\Delta_h \log(y_{s,t+h}) = \alpha^h + \beta^h MPS_t \times \mathbb{1}FSCP_{s,t-1} + \theta^h \mathbb{1}FSCP_{s,t-1} + \alpha_s^h + \alpha_t^h + \epsilon_{s,t}^h. \tag{4.3}$$

where $\Delta_h \log(y_{s,t+h}) \equiv \log(y_{s,t+h}) - \log(y_{s,t-1})$ is the cumulative log change in the Producer Price Index (PPI) for the 4-digit NAICS industry level s between quarters $t-1$ and $t+h$. The term $MPS_t \times \mathbb{1}FSCP_{s,t-1}$ interacts the monetary policy shock MPS_t with a high-pressure indicator $\mathbb{1}FSCP_{s,t-1}$, which is an indicator variable that equals one if sector s's supply chain pressure at the end of period $t-1$ is above its historical mean, capturing whether the sector is experiencing unusual supply chain pressure.[12] The coefficient β^h thus measures the additional PPI response in sectors under unusual supply chain pressure. The fixed effects α_s^h and α_t^h absorb time-invariant sector characteristics and common quarterly shocks, respectively. I cluster standard errors at the 4-digit NAICS industry level.

Figure 4 plots the differential cumulative PPI response between high- and low-pressure sectors following the shock. The response displays a hump-shaped pattern, reaching its maximum two quarters after the shock. High-pressure sectors experience an additional 1.56% price increase relative to unconstrained sectors before dissipating by six quarters post-shock. When input deliveries are constrained, firms face higher marginal costs as they compete for limited materials. To preserve their profit margins amid rising demand, these firms pass these costs onto consumers through higher prices. In contrast, unconstrained firms can meet the increased demand by acquiring more inputs at relatively stable costs, which dampens their price responses. This mechanism is consistent with the findings of Balleer and Noeller (2023), who utilize German firm-level survey data on raw material shortages. Their work shows that constrained firms are more likely to adjust their prices following an expansionary monetary shock than their unconstrained counterparts.

[12] To construct the supply chain pressure measure for sector s at time t, I aggregate firm-level pressures within each sector using market capitalization weights.

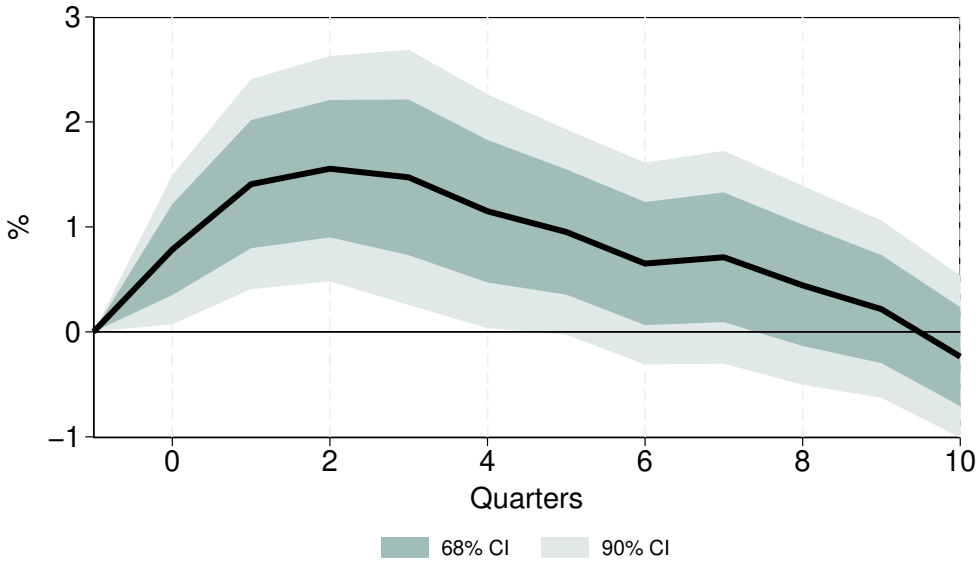


Figure 4: The Effect of Monetary Policy on Prices: Supply Chain-Pressured vs. Non-Pressured.

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in the PPI at the NAICS-4 digit level in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on sectors experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.3. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the sector level. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in the PPI.

Robustness checks: In Appendix D, I re-estimate Equation 4.3 using alternative measures of supply chain pressure instead of the binary indicator based on a sector's historical mean. I also exclude the surge in supply chain pressures following COVID-19. I test alternative U.S. monetary policy shock series from the literature. Additionally, I replicate the analysis using firm-level markup estimates. While the results are qualitatively similar, they should be interpreted with caution for the reasons mentioned earlier.

5 Model

In this section, I outline the key ingredients of the New Keynesian model that includes supply chain pressures. Households derive utility from consumption and incur disutility from labor. They supply labor in perfectly competitive markets and make intertemporal consumption-saving decisions, subject to a budget constraint. The central bank, in turn, sets the nominal policy rate according to a standard Taylor rule, responding to deviations in inflation and output.

There are four different types of firms operating along the production chain. First, a

perfectly competitive final goods firm aggregates retail output into a single consumption-investment good. Second, a continuum of retail firms repackages wholesale goods and resells them to the final goods firm. These retail firms behave as monopolistic competitors and are subject to price stickiness. Third, a representative intermediate producer hires labor in perfectly competitive markets to manufacture the inputs demanded by the wholesale sector. Fourth, a representative wholesale firm combines its accumulated capital stock (determined by the capital accumulation equation) with purchased intermediate inputs to produce output.

The key departures from a standard framework involve the wholesale firms, which are subject to supply chain pressures that impact the productivity of the intermediate inputs purchased from the intermediate sector. Therefore, I focus on that in this text. The rest of the model is presented in detail in Appendix E.

5.1 Wholesale Production

The representative wholesale firm uses a Cobb–Douglas technology

$$Y_{mt} \;=\; \left(M_t^{\text{eff}}\right)^{1-\alpha} K_t^{\alpha} \tag{5.1}$$

where K_t represents the predetermined stock of physical capital and M_t^{eff} denotes the effective amount of intermediate inputs used in production.

Effective intermediate inputs: The wholesale firm places an order and pays $P_{M,t}$ for each unit M_t ordered of intermediate inputs. However, under supply chain pressures captured by the parameter S, not all these inputs arrive on time or in usable condition. Therefore, I introduce the "effective" input.

$$M_t^{\text{eff}} \;=\; \Phi(M_t, S), \tag{5.2}$$

Intuitively, when a firm orders intermediate goods, some of the shipment may spoil during supply chain delays, leaving only M_t^{eff} units available for production. The function Φ maps the ordered quantity M_t and the supply chain pressure state S into the effective input M_t^{eff}, thereby capturing the loss of usable inputs.

The function $\Phi(M_t, S)$ must satisfy several properties. First, it normalizes to the ordered quantity without bottlenecks: $\Phi(M_t, 0) = M_t$. Second, effective inputs lie strictly between zero and the amount ordered. Third, it is strictly increasing in orders and strictly decreasing in supply chain pressure. Fourth, the marginal efficiency of an extra unit is

positive but never exceeds one, reflecting that each ordered unit yields at most one usable unit. Fifth, tighter bottlenecks never make an extra order more productive. Finally, the inequality condition $\Phi_M(-\Phi_S) \geq \Phi(-\Phi_{MS})$ guarantees that the percentage increase in effective inputs produced by an extra unit of materials is at least as large as the percentage increase in the marginal damage inflicted by supply chain pressures. Economically, this rules out situations in which supply chain disruptions erode the gains from ordering more inputs faster than those gains materialize. Consequently, even during periods of supply chain pressure, firms still find it worthwhile to accumulate materials, and the production function remains well-behaved (quasi-concave) rather than exhibiting "no-buy" corners in optimal solutions.[13]

The wholesale firm sells its product to retail firms for $P_{m,t}$, pays P for the investment good, and capital depreciates by δ. Its nominal dividend is

$$\Pi_t^W = P_{mt}\big(\Phi(M_t, S)\big)^{1-\alpha} K_t^{\alpha} - I_t - P_y^M M_t,$$

the firm maximizes the present discounted value of real dividends using the household's stochastic discount factor. The first order conditions are

$$p_{m,t}(1-\alpha)\left[\Phi(M_t, S)\right]^{-\alpha} K_t^{\alpha}\, \partial_M \Phi(M_t, S) = \; p_t^M \tag{5.3}$$

$$1 \;=\; E_t \Lambda_{t,t+1}\Big[p_{m,t+1}\,\alpha \Phi(M_{t+1}, S)\big]^{1-\alpha} K_{t+1}^{\alpha-1} \;+\; (1-\delta)\Big] \tag{5.4}$$

$p_{m,t} = P_{m,t}/P_t$ is the relative price of wholesale output, and $p_t^M = P_t^M/P_t$ is the relative price of inputs ordered. Equilibrium condition (5.3) is the first order condition for intermediate inputs, while (5.4) is the optimality condition for capital.

Suppose an expansionary monetary policy shock raises the wholesale output price $p_{m,t}$, forcing the wholesale firm to decide whether to meet the extra demand with additional intermediate inputs or by expanding the capital stock. I show below that tighter supply chain pressures S dampen the input-price elasticity, while the capital-price elasticity remains unchanged. Therefore, the firm reallocates the adjustment margin toward capital when bottlenecks tighten.

[13] Appendix E.6 shows that this last condition is necessary to produce a decrease in input-price elasticity when supply chain pressures increase.

Input–price elasticity under supply chain pressures. Define the log-elasticity of orders with respect to the wholesale price as follows:

$$\varepsilon_{M,p}(S) \equiv \frac{\partial \ln M_t}{\partial \ln p_{m,t}} = \left(\alpha \frac{\Phi_M(M_t, S)}{\Phi(M_t, S)} - \frac{\Phi_{MM}(M_t, S)}{\Phi_M(M_t, S)}\right)^{-1}.$$

Under the baseline properties of the the function $\Phi\big(M_t, S\big)$ it follows that

$$\frac{\partial \varepsilon_{M,p}(S)}{\partial S} < 0 \quad \text{for } S > 0,$$

so tighter bottlenecks make firms less willing to vary intermediate inputs in response to a given price increase.

Capital–price elasticity under supply chain pressures. Following similar steps, it can be shown that $\varepsilon_{K,p}(S) = \frac{1}{1-\alpha}$, which is independent of S. Therefore, $\frac{\partial \varepsilon_{K,p}(S)}{\partial S} = 0$. The detailed algebra is provided in Appendix E.6.

Implication for the firm's adjustment margin. As a result, when an expansionary monetary shock raises wholesale prices, companies experiencing supply chain pressures find that additional inputs are significantly less productive. The combination of higher demand with the supply chain friction pressures increases the relative attractiveness of capital, leading firms to shift their focus from using additional inputs to investing in physical capital.

5.2 Intermediate Input Sector

A representative competitive producer of intermediate inputs converts labor one-for-one into the intermediate good, so the production technology is simply $M_t = L_t$. Each period the firm sells its output to wholesale firms at the nominal price P_t^M and hires labor at the nominal wage W_t. Hence nominal dividends in period t are $\Pi_t^I = P_t^M L_t - W_t L_t$. The firm chooses L_t to maximize the present discounted value of real dividends, using the stochastic discount factor of the household for intertemporal valuation.

Optimality requires that the marginal revenue of an additional unit of labor equal its marginal cost once both are expressed in real terms. Dividing by the aggregate price level P_t yields the following equilibrium condition

$$p_t^M = w_t \tag{5.5}$$

where $p_t^M \equiv P_t^M / P_t$ is the relative price of the intermediate good and $w_t \equiv W_t / P_t$ is the real wage. The equilibrium condition (5.5) equates the firm's marginal revenue product of labor with the real wage, ensuring that in equilibrium the marginal cost of producing an extra unit of the intermediate input equals its marginal benefit.

Calibration: The model is calibrated at a quarterly frequency using parameter values that are standard in the New Keynesian literature (Sims and Wu, 2021; Sims et al., 2023). All parameter choices are summarized in Table E.1. The only non-standard parameter is the supply chain pressure index S. Without loss of generality, I adopt a linear penalty function form:

$$\Phi(M_t, S) \;=\; M_t \;-\; S, \qquad 0 \leq S < M_t,$$

which satisfies all the properties laid out previously. The benchmark calibration fixes $S = 0$ (no bottlenecks), and I perform a sensitivity analysis for expansionary monetary policy shocks over the range $S \in \{0.25, 0.5, 0.75\}$.[14]

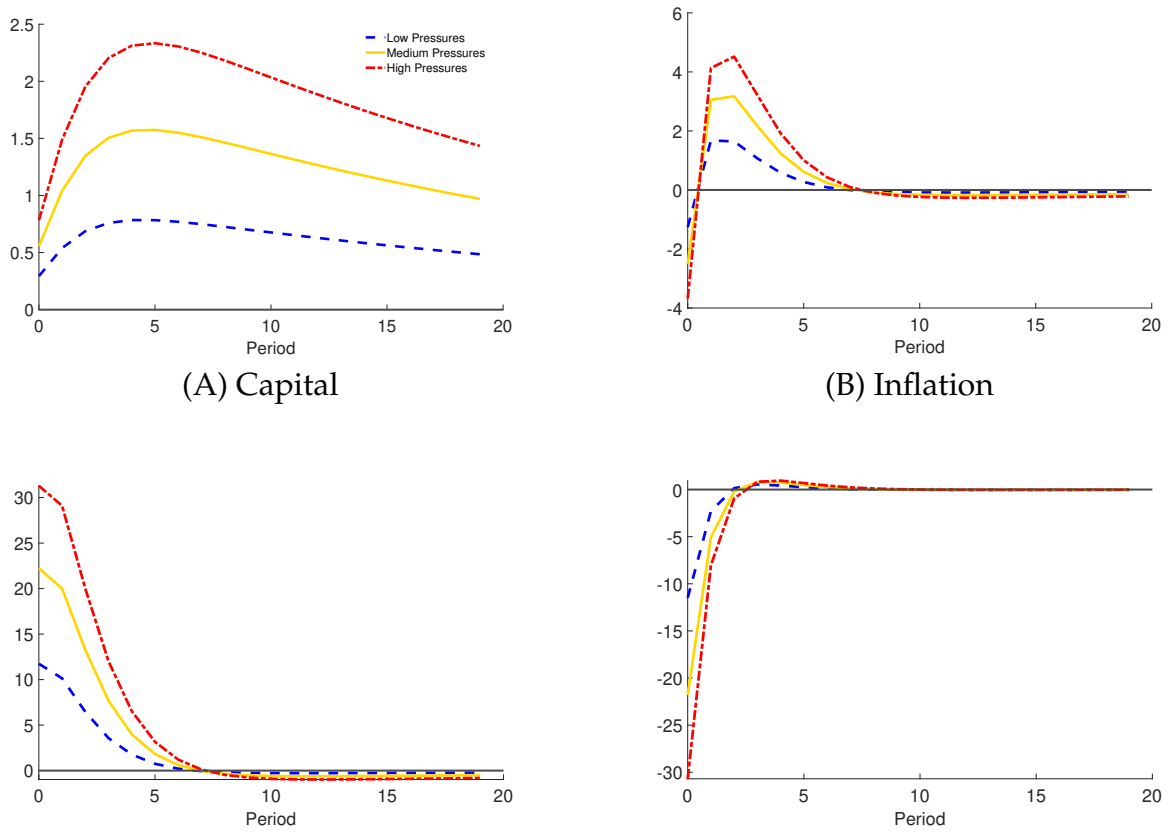
5.3 Model Predictions

In this section, I quantify how supply chain pressures affect the transmission of a monetary policy shock by comparing the dynamic responses of capital, inflation, investment, and intermediate inputs in an economy under supply chain strain versus a frictionless baseline. Figure 5 illustrates the differences between these impulse response functions. Capital, investment, and intermediate inputs are measured in basis points, while the inflation responses represent the annualized differences in quarterly inflation, also expressed in basis points. By subtracting the baseline responses from those in the pressured economy, the figure highlights the additional impact of supply chain constraints in the transmission of monetary policy.[15]

To generate these differentials, I impose an unanticipated annualized cut of 100 basis points to the policy rate through the Taylor rule. The model is then simulated under three supply chain pressure scenarios: low, medium, and high, alongside a baseline case with no disruptions. Each plotted line represents the difference between a pressured

[14] While the linear specification is transparent and keeps the number of new parameters to a minimum, the framework can accommodate alternative shapes as long as they satisfy the features described earlier. An alternative choice is $\Phi(M_t, S) = M_t - S\, M_t^{\eta}$ with curvature parameter $\eta > 0$. However, this type of function requires an additional calibration step for η.

[15] Figure E.1 plots the impulse responses of the main variables in the baseline economy, rather than their differentials for the same sized shock. These magnitudes are broadly in line with the effects of monetary policy shocks estimated in several papers (Christiano et al., 2005; Sims and Wu, 2021; Sims et al., 2023).



(A) Capital (B) Inflation

(C) Investment (D) Inputs

Figure 5: Model Predictions and Differential Responses Under Supply Chain Pressures

Notes: Each line shows the differential impulse response obtained by subtracting the baseline economy without bottlenecks from an economy with low (dashed blue lines), medium (solid yellow lines), and high (dash-dotted red lines) supply chain pressures. The shock is an unanticipated 100-basis-point cut to the annualized policy rate. Panel A shows the additional cumulative change in the log capital stock, Panel B plots the corresponding change in quarterly inflation, Panel C displays the differential response in investment, and Panel D reports the gap in intermediate inputs. The horizontal axis measures periods in quarters, and the vertical axes are in basis points.

economy's response and the baseline: dashed blue for low pressures, solid yellow for medium pressures, and dash-dotted red for high pressures. This approach aligns with the empirical strategy outlined in Section 4, providing a direct comparison between the empirical results and the simulation outcomes regarding monetary transmission under supply chain frictions.

Panel A shows the percentage deviation of the capital stock, K_{t+h}, from the frictionless benchmark at each horizon h. The capital accumulation gap reaches its highest point in the fourth quarter and increases in intensity with varying levels of supply chain pressure. The deviations are approximately 0.78 basis points above the benchmark under low pressure,

1.57 under medium pressure, and 2.31 under high pressure.[16] These additional effects correspond to an amplification of the monetary policy shock of about 16%, 32%, and 47%, respectively, relative to the baseline economy without bottlenecks. While the gap gradually narrows, it remains positive throughout the entire five-year horizon. This dynamic implies that accommodative monetary policy during high-pressure episodes can generate a permanent expansion in the capital stock, yielding persistent gains in the economy's productive capacity.

Panel B plots the differential cumulative inflation response between high- and low-pressure states following the same expansionary monetary policy shock. The figure exhibits a positive hump-shaped pattern that is similar to Figure 4. The additional inflation peaks two quarters after the shock, reaching approximately 1.65 basis points, 3.18 basis points, and 4.52 basis points for each of the three intensities of disruptions. These values imply amplification factors of approximately 17%, 33%, and 47%, respectively. After six quarters, there is no differential response in inflation, and prices evolve almost identically to the frictionless case. The result corroborates that policymakers face a trade-off: accommodating monetary policy during episodes of high supply chain pressure can secure larger and more persistent capacity gains, but at the cost of a short-lived spike in inflation.

Panel C shows the differential response in investment. The impact intensifies with higher levels of supply chain strain, reaching 11.74 basis points under low pressure, 22.25 under medium pressure, and 31.3 under high pressure. These magnitudes translate to amplification effects of approximately 9.1%, 17.2%, and 24.2%, respectively. This indicates that firms facing tighter supply chain constraints increase investment more aggressively in response to expansionary policy, likely as a way to alleviate bottlenecks and expand productive capacity.

Panel D reports the gap in intermediate inputs ordered by firms, relative to the baseline. In contrast to the other variables, inputs decline with rising supply chain pressures: –11.49 basis points under low pressure, –21.8 under medium pressure, and –30.69 under high pressure. These declines represent attenuations of input usage by approximately –15.4%, –29.2%, and –41.2%, respectively, relative to the response in the baseline economy. The negative differential reflects how bottlenecks constrain firms' ability to scale up input purchases despite looser monetary conditions. As a result, the marginal contribution of inputs to production diminishes, reinforcing firms' reliance on capital to meet rising demand.

Panels C and D together highlight a key substitution mechanism in the model. In-

[16] I report these gaps in basis points because the underlying deviations are small in percentage terms, yet they represent an economically meaningful amplification of the monetary policy shock.

vestment rises while inputs fall, with both exhibiting similar absolute magnitudes across pressure states but opposite signs. This dynamic arises because supply chain frictions reduce the elasticity of input orders with respect to higher demand, making capital a more attractive margin of adjustment when bottlenecks bind. As supply chain pressures intensify, firms compensate for lower effective intermediate inputs by increasing investment in capital. As a result, wholesalers increasingly rely on physical capital to meet rising demand following an expansionary shock. The model thus illustrates how supply frictions reshape the transmission of monetary policy shifting it away from short-run input scaling and toward longer-run capital accumulation. The simulations align closely with the empirical firm-level evidence presented in Section 4 and highlights the state-dependent effects of monetary policy.

6 Conclusion

This paper demonstrates that supply chain frictions significantly influence the transmission of monetary policy. I have developed a unique firm-level supply chain pressure index using natural language processing techniques. Utilizing this index, I show that an expansionary monetary policy shock leads to much larger tangible capital accumulation among firms facing significant supply chain constraints compared to their less constrained counterparts. Several supporting analyses confirm that these constrained firms tend to substitute scarce intermediate inputs with capital. At the sector level, industries facing input constraints pass a greater share of monetary accommodation into prices, resulting in an additional Producer Price Index increase that lasts for approximately six quarters.

A stylized New Keynesian model that incorporates supply chain pressures affecting the effectiveness of intermediate inputs helps replicate these empirical patterns. When supply chain pressures are high, inputs become less effective, and investment in capital becomes a means to satisfy rising demand when inputs are scarce. Simulated impulse responses closely align with the data: tighter bottlenecks amplify investment and create an additional hump-shaped inflation that dissipates after six quarters.

The results indicate that the effectiveness of monetary policy varies depending on the state of the economy. When supply chain bottlenecks are present, lowering interest rates can encourage increased productive capacity and help reduce inflationary pressures in the medium term; however, this may result in a larger short-term increase in prices. In contrast, the same stimulus tends to have weaker real effects when the economy is not constrained.

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Appendix For Online Publication

This online appendix is organized as follows. Appendix A describes in more detail the data construction. Appendix B explains the natural language methods. Appendix C displays additional information about the index validation. Appendix D presents robustness exercises related to the empirical assessment of monetary policy transmission under supply chain pressures. Appendix E has additional details on the theoretical part.

A Data construction

A.1 Matching transcripts to firm's balance sheet

Table A.1: Matching Earnings Call Transcripts with Compustat Details

Steps	Number of Transcripts
Transcripts from CapitalIQ	197,265
Matched with Ticker	161,204
Matched by hand collecting	35,046
Transcripts not Matched	1,015
Final Sample	196,250

Notes: This table displays the breakdown of the matching procedures between earnings calls transcripts and the Compustat North America Fundamentals Quarterly.

A.2 Firm-level balance sheet data

This subsection outlines the firm-level variables used in the empirical analysis, derived from quarterly Compustat data, along with the sample selection criteria.

Data Construction: All nominal variables are deflated using the GDP deflator provided by the Bureau of Economic Analysis, except for the PPE, which is deflated by the investment-specific GDP deflator. I winsorize continuous variables at the 1st and 99th percentiles of their respective distributions. I fill one-quarter gaps in the firm-specific series of these variables by linear interpolation (including the firm-level supply chain index).

1. *Capital stock*: to construct a measure of the firms' physical capital stocks I apply a perpetual inventory method, as is usually done for Compustat data (Ottonello and Winberry, 2020; Meier and Reinelt, 2022; Jeenas, 2023). I measure the initial value of firm i's capital stock as the earliest available level of gross plant, property, and

equipment ($\text{ppegtq}_{i,t}$). From this period onwards, I calculate the evolution of $k_{i,t+1}$ using the changes in net plant, property, and equipment ($\text{ppentq}_{i,t}$) as

$$k_{i,t+1} = k_{i,t} + \texttt{pptenq}_{i,t+1} - \texttt{pptenq}_{i,t}.$$

2. *Physical capital investment:* it is defined as $\Delta \log(k_{i,t+1})$, where $k_{i,t+1}$ denotes the physical capital stock of firm i at the end of period t.

Sample Selection: I exclude the following observations:

1. Firms in the following sectors: utilities (NAICS 2-digit code equal to 22) finance, insurance, and real estate sectors, (NAICS 2-digit code equal to 52 or 53), and public administration (NAICS 2-digit code equal to 99)
2. Firms with headquarters not incorporated in the United States.
3. Negative capital, assets, or sales.
4. Missing capital, assets, sales, or cash holdings.
5. Quarterly real sales growth above 1 or below -1.
6. Cash holdings greater than total assets

B Textual Analysis

Appendix B.1 shows the dictionary used in the initial step of the methodology described in Section 3, along with a detailed explanation of how the supply chain dictionary was constructed. Appendix B.2 details the four sentence classification methods: Bag-of-Words, BERT, RoBERTa, and FinBERT.

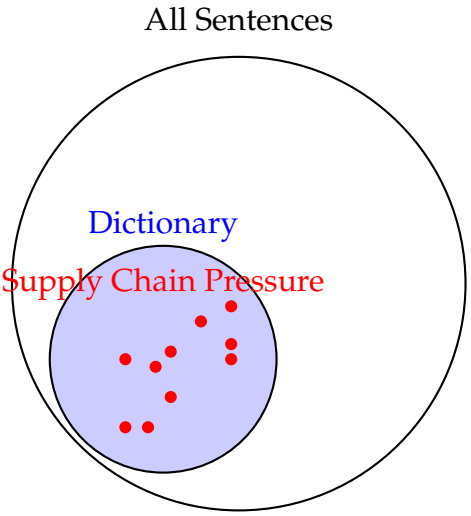
B.1 The Supply Chain Dictionary

Table B.1: Supply Chain Pressures Dictionary

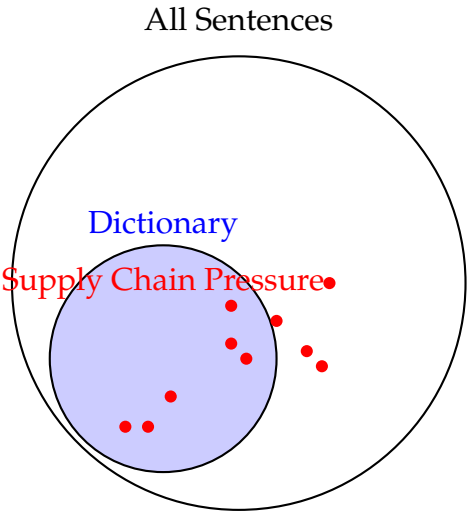
availability, bottleneck, bottlenecks, capacity constrained, capacity constraints, freight cost, freight costs, freight expenses, freight issues, freight premium, inbound freight, lead times, logistic, logistics, port congestion, port congestions, port delays, production constraint, production constraints, production delay, production delays, shortage, shortages, supplier, suppliers, supplies, supply, supply chain, shipment, shipping, vendor, vendors, vessel

Notes: This table lists the keywords used to filter to potential sentences associated with supply chain pressures.

Creating the dictionary: As mentioned in the main text, the first step in isolating supply chain pressure information from our sentence-level dataset is a dictionary-based filtering procedure. Figure B.1 illustrates this step in the methodology. In Panel A, the large circle represents all sentences in the corpus, the nested blue circle shows the subset selected by our keyword dictionary, and the red dots pinpoint those sentences that truly convey supply chain pressures. Panel B illustrates the danger of an under-specified dictionary: important pressure-related sentences lie outside the filter, resulting in false negatives that no downstream classifier can recover. This visualization highlights why constructing and rigorously validating a comprehensive supply chain pressure dictionary is essential before applying more advanced language models.



(A) Preselection and Classification of Supply Chain Sentences



(B) Potential Gaps in Dictionary Filtering

Figure B.1: Illustration of Sentence Filtering and Classification Process

Notes: Panel A illustrates the preselection process, where a dictionary filters (blue circle) all sentences to identify those related to supply chain pressures. The innermost red circle represents sentences classified as expressing supply chain pressures. Panel B highlights potential gaps in dictionary filtering, where sentences outside the dictionary-filtered area may still pertain to supply chain pressures but are missed due to a inaccurate dictionary applied.

I applied an iterative model, as proposed by Grimmer et al. (2022) to discover relevant keywords for the filtering dictionary. Figure B.2 exemplifies this process. I start with a preliminary dictionary to collect 1,000 random sentences that contain at least one keyword from this dictionary.[17] These sentences are then subjected to a topic model using Latent Dirichlet Allocation (LDA) (Blei et al., 2003).[18] I analyze these clusters to understand what types of sentences are being grouped together.

Based on insights gained from the topic model, I refine the dictionary by updating it with new words or expressions that better capture supply chain pressures in firms' communication. For instance, certain terms frequently appear in supply chain-related clusters and are relevant to supply chain pressures but were not part of the original dictionary. I incorporate them to improve the accuracy of filtering. For ease of interpretation, Figure B.3 illustrates the first output of this iterative process. The word cloud highlights terms such as "shortage" and "production delays" that are indicative of supply chain constraints. After confirming their relevance in sentence contexts, these terms are added to the dictionary to enhance its ability to capture firms' supply chain pressures.

I continue this interactive process to refine the dictionary, allowing for more accurate identification of supply chain-relevant sentences over time. When this discovery process stops producing potential new keywords, I randomly sample an additional 1,000 sentences from 2022 calendar year, which is the year with the highest level of supply chain pressure in the sample (see Figure C.12). By focusing on this year, the results likely underestimate the dictionary's performance, as the high prevalence of supply chain pressure-related sentences increases the likelihood of missing some. Therefore, if the dictionary performs well under these conditions, the results represent a lower bound on its effectiveness.

Then, I classify these additional sentences as either supply chain pressure–related or not. Out of the total sentences labeled, fifteen are related to supply chain pressures and only one is classified as supply chain pressure–related but does not contain any dictionary word.[19] This ratio corroborates that, with the final dictionary, the probability of missing a supply chain–pressure sentence is no greater than 0.1% (1 out of 1,000).

This step helps evaluate the effectiveness of the dictionary by calculating the rate of

[17]The initial supply chain dictionary contain the following words "supply chain.", "supply chains", "supply", and supplies".

[18]LDA is a generative statistical model that assumes each sentence is a mixture of topics, and each topic is a mixture of words. LDA clusters the sentences into different groups based on the co-occurrence of words.

[19]As a robustness check, I use the fine-tune language model described in Section 3.3 to classify additional 1,000 random sentences that do not contain any dictionary term. The language model understand the synonyms. Therefore, it has the ability to pull up sentences that discuss similar concepts in different ways. The total number of sentences classified as supply chain pressure-related is eight. Out of those sentences, only two are actually related to supply chain pressures.

supply chain–related sentences that the dictionary misses. The goal is to reach a point where the dictionary captures a high proportion of relevant instances and misses very few. If, after annotating a large random sample, I find that very few supply chain-relevant sentences are missed, it suggests the dictionary is sufficiently comprehensive. The stopping criterion is essentially based on achieving a favorable ratio—where a significant number of instances are captured by the dictionary, and very few relevant sentences are left uncaptured. While it's impossible to prove that all relevant sentences are covered, this process helps bound the error and ensure the dictionary is robust."

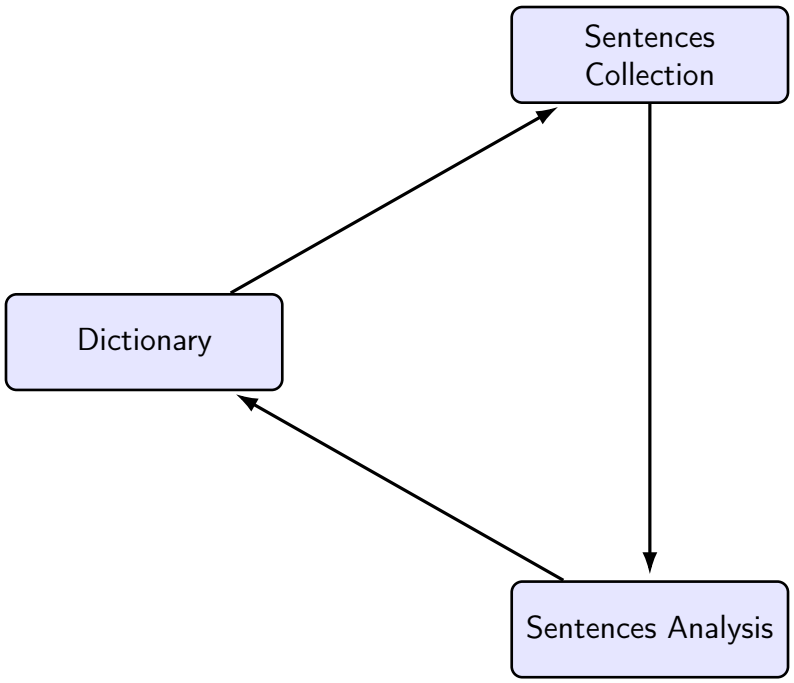


Figure B.2: Elaborating the Dictionary: A Iterative Model

Notes: This figure illustrates the iterative model proposed by Grimmer et al. (2022) and adapt the process for constructing the dictionary used in the initial step of the methodology described in Section 3.

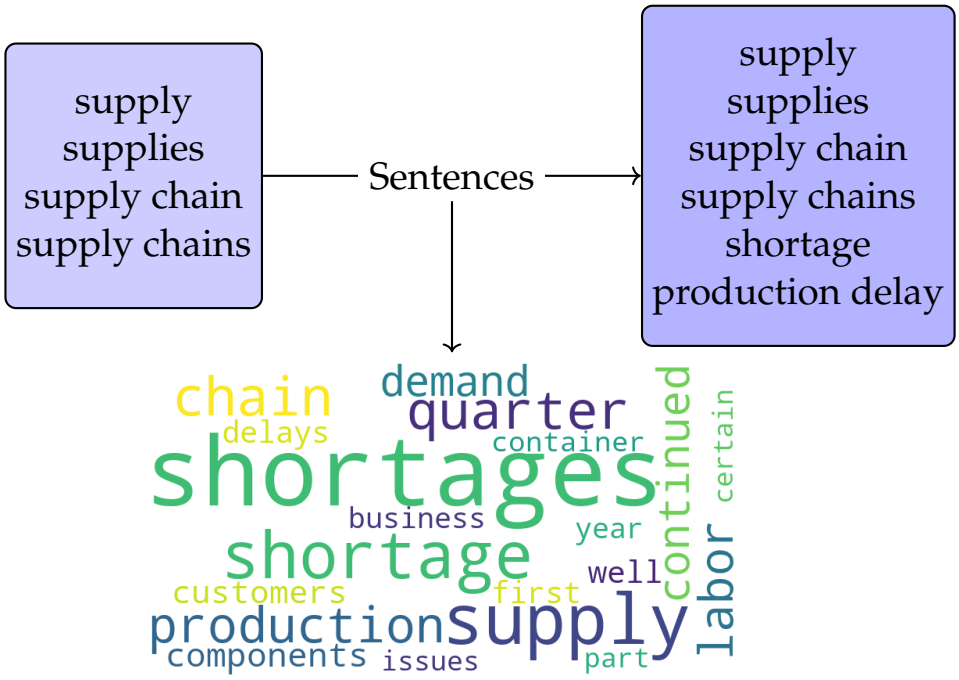


Figure B.3: Constructing the Dictionary: First Iteration

Notes: This figures plots two examples of LDA output for sentences initial 1,000 sentences containing at least one words of the following “supply chain.", “supply chains", “supply", and supplies".

B.2 NLP Classification Methods

Bag-of-Words: this method involves the construction of a list of keywords related to a topic of interest, "the dictionary". The method counts the frequency with which these words are used in the entire text.[20] These dictionaries are widely used because they provide a straightforward way to gather information. However, their usefulness may be restricted by the range of topics they cover and their capacity to interpret nuances and context.

The index using the bag-of-words method is calculated as the number of sentences containing at least one word from the "Supply" dictionary and at least one word from the "Pressures" dictionary, divided by the total number of sentences in the transcript. The "Supply" and "Pressures" dictionaries are those used in the Supply Bottlenecks Index (SBI) based on newspaper data (Burriel et al. (2023)).

$$\text{Firm Supply Chain Pressure Index}_{it} = \frac{\sum \text{Sentences with Supply} \bigcap \text{Pressure}_{it}}{\sum \text{Sentences}_{it}}$$

Bidirectional Encoder Representations from Transformers (BERT): is a pre-trained language model based on the transformer architecture. It is trained using a masked language modeling objective on large amounts of text data, and is widely used for natural language tasks. Thanks to its bidirectional nature, BERT considers context from both the left and right of each word in a sentence, making it highly effective for various NLP applications. It generates context-aware word embeddings, meaning that a word's representation depends on its surrounding context. This contrasts with earlier models like Word2Vec and GloVe, which produce static embeddings regardless of context.

BERT can be fine-tuned on specific downstream tasks using labeled data. Fine-tuning BERT allows for making predictions, solving specific NLP problems, or classifying sentences. For more details, see Devlin et al. (2018).

Robustly Optimized BERT Approach (RoBERTa): is an optimized version of BERT that incorporates several key changes in the pre-training process. First, it is trained on a larger dataset and requires more computational resources and training steps. Second, it applies dynamic masking rather than static masking, meaning the masked tokens change during training epochs. Third, RoBERTa eliminates the next sentence prediction task, focusing solely on the Masked Language Model (MLM) task. In general, RoBERTa outperforms BERT on various NLP benchmarks due to these optimizations. For more details, see Liu et al. (2019).

[20] Some papers count the frequency of the sentences in which these words appeared.

FinBERT: is a specialized version of BERT for the financial sector. It is trained on financial documents such as earnings reports, analyst reports, and news articles. However, the core architecture remains similar to BERT. What changes is the pre-training corpus. For more details, see Araci (2019).

C Additional Details on the Validation

Appendix C.1 presents a detailed validation of the sentence-level classifiers. Appendix C.2 validates the FSCP indicator at the firm level using several "ground truth" events such as natural disasters that generated pronounced supply chain disruptions. It also shows descriptive statistics of the index and describes the standardization of the FSCP indicator at the firm level to isolate unusual pressures from systematic supply chain problems. Appendix C.3 validates the FSCP index at the aggregate level.

C.1 Sentence Level

This section defines the core evaluation metrics used to compare the models: Accuracy, Precision, Recall, Specificity, and the F1 Score.
Accuracy measures the overall proportion of correct predictions. It is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where:

- True Positives (TP): Number of correctly predicted positive sentences.
- True Negatives (TN): Number of correctly predicted negative sentences.
- False Positives (FP): Number of incorrectly predicted positive sentences.
- False Negatives (FN): Number of incorrectly predicted negative sentences.

Precision measures the accuracy of the positive predictions made by the model. It is defined as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall measures the ability of the model to correctly identify positive instances. It is defined as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

Specificity: measures the ability of the model to correctly identify negative instances. It is defined as:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

F1 Score is the harmonic mean of Precision and Recall, providing a single metric that balances both. It is particularly useful when the class distribution is imbalanced. The F1 Score is defined as:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table C.1: Comparison of True and False Positives/Negatives across Bag-of-Words, BERT, RoBERTa, and FinBERT models.

		Human Judgment	
		Positive	Negative
Bag-of-Words	Positive	**True Positive (87)**	**False Positive (30)**
	Negative	**False Negative (270)**	**True Negative (613)**
BERT	Positive	**True Positive (309)**	**False Positive (34)**
	Negative	**False Negative (48)**	**True Negative (609)**
RoBERTa	Positive	**True Positive (315)**	**False Positive (24)**
	Negative	**False Negative (42)**	**True Negative (619)**
FinBERT	Positive	**True Positive (315)**	**False Positive (49)**
	Negative	**False Negative (42)**	**True Negative (594)**

Notes: The table shows the True and False Positives/Negatives across Bag-of-Words, BERT, RoBERTa, and FinBERT models in the out-of-sample validation of 1,000 randomly selected sentences containing at least one word from the dictionary (see Table B.1 for the list of words).

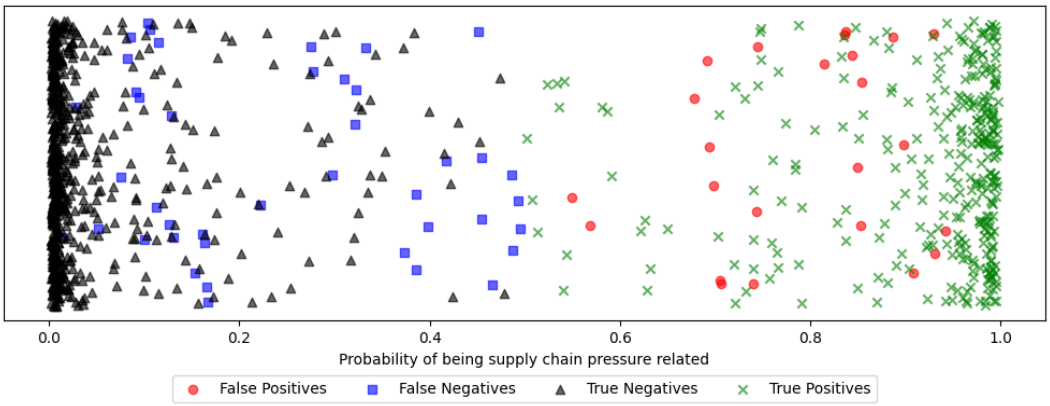


Figure C.1: Error Analysis of RoBERTa Classification

Notes: Each marker represents one of the 1,000 sentences in the validation set, plotted at its predicted probability of belonging to the supply chain-pressure class on the horizontal axis. Red circle markers denote false positives; blue square markers denote false negatives; black triangle markers denote true negatives; and green cross markers denote true positives.

C.2 Validation at the firm-level

In this section, I concentrate on firm-level validation exercises. As noted in the main text, strong sentence-level classification performance does not necessarily translate into accurate firm-level measures once aggregated. Therefore, firm-level validation must target tasks that align closely with the underlying economic concept (Ganguli et al., 2024). I use "ground truth" events—such as natural disasters—that produced well-documented supply chain disruptions for exposed firms. I begin with an in-depth analysis of China's COVID-19 shutdown in early 2020 and then apply the same difference-in-differences framework more succinctly to the following "ground truth" events: the China Earthquake in 2008, Eyjafjallajökull volcanic eruption in 2010, Tōhoku earthquake in Japan in 2011, the Philippines Typhoon in 2013, the Brazil truck drivers strikes in 2018, and the Trade War between US and China in 2018-2019.

C.2.1 China's COVID-19 Shutdown in 2020

Context: Figure C.2 plots the total imports in millions of dollars from China by quarter, as collected by the United States Census Bureau. We can observe a significant decline in imports from China in 2020Q1 that quickly rebounds in the following quarter. Heise (2020) and Meier and Pinto (2024) show that this decline was not observed in imports from other countries. Consequently, if firms were importing inputs directly from China right before the start of these shutdowns, the FSCP index should capture significant supply chain pressures in the first quarter of 2020.

I replicate the Hoberg and Moon (2017) offshore activities dataset focusing exclusively on firms that reported direct imports in their 10-K filings by the end of the 2019 fiscal year. The dataset captures how many times a given firm mentions offshore input activities (the firm purchases inputs from a given nation).[21] Firms mentioning buying inputs from China at the end of the 2019 fiscal year comprise the treatment group exposed to the shutdown, while firms that do not mention purchasing inputs from China comprise the control group not exposed to the event.

I run the following difference-in-difference specification:

$$FSCP_{it} = \sum_{l=-3}^{4} \beta_l (Treat_i \times Quarter_t) + \gamma Z_{i,t} + \theta_t + \psi_i + \gamma_s + \epsilon_{it} \tag{C.1}$$

[21] Hoberg and Moon (2017) offshore activities dataset contains four specific activities: (1) Offshore Output (firm sells goods to given nation), (2) Offshore Input (firm purchases inputs from given nation), (3) Offshore External Input (firm purchases inputs from given nation but does not own assets there), and (4) Offshore Internal Input (firm purchases inputs from given nation and the firm does own assets in the given nation).

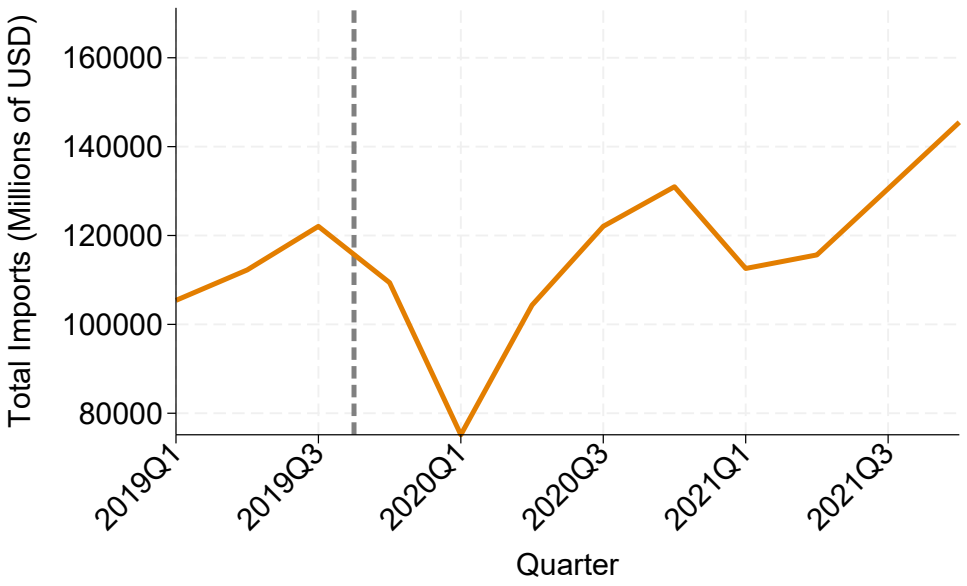


Figure C.2: Total U.S. Imports from China

Notes: This figure plots the total U.S. imports in millions of dollars from China by quarter. The data is from United States Census Bureau. The vertical line indicates the beginning of the COVID-19 pandemic.

Where $FSCP_{i,t}$ is the standardized supply chain pressure for firm i at quarter t. $Treat_i$ is a dummy that equals one if the firm imported inputs from China immediately before the event, and it is zero otherwise. $Quarter_t$ is a set of quarterly time dummies capturing each quarter relative to the event, allowing for the measurement of treatment effects over time. $Z_{i,t}$ is a vector of firm-level characteristics which include: leverage, size, sales growth, age, inventories over assets, cost of goods sold growth, and cash-flow. θ_t ψ_i, γ_s are time, firm, and sector s fixed effects, respectively.

If the FSCP accurately captures unusual firm-level supply chain pressures, the coefficient β_l should be positive and statistically significant in 2020Q1. This finding is consistent with previous literature (Heise, 2020; Meier and Pinto, 2024) and aligns with the sharp decline in Chinese imports. Figure C.3 displays the β_l coefficients, where firms directly purchasing inputs from China experienced a 0.39 standard deviation increase in supply chain pressure compared to the control group in 2020Q1. Table C.2 conducts a pre-treatment F-test to rigorously check for pre-trend. Figure C.4 tests alternative specifications that include firm fixed effects and time-sector fixed effects. It also accounts for potential within-industry correlation in ϵ_{it} by clustering standard errors at the industry level.

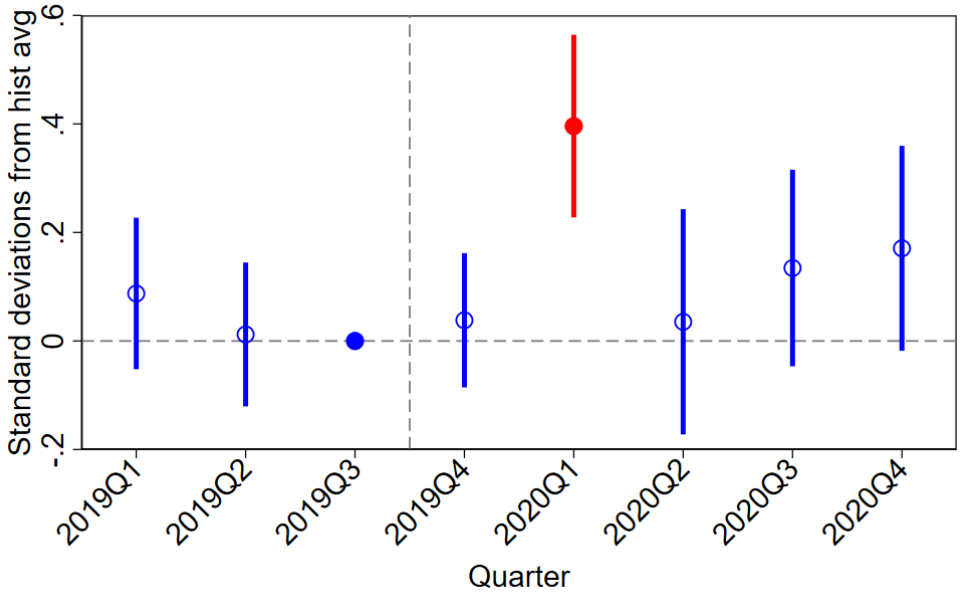


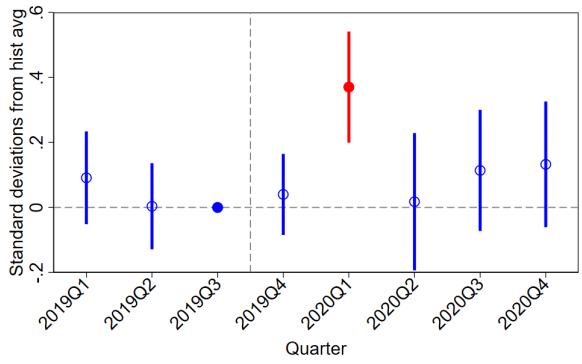
Figure C.3: Validation at the firm-level: China's COVID-19 Shutdown in 2020

Notes: This figure reports β_l coefficients of Equation C.1. The dummy *Treat* equals one if a firm import inputs from China immediately before the COVID-19 pandemic begins in December 2019, and zero otherwise. The vertical line indicates the beginning of the COVID-19 pandemic. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

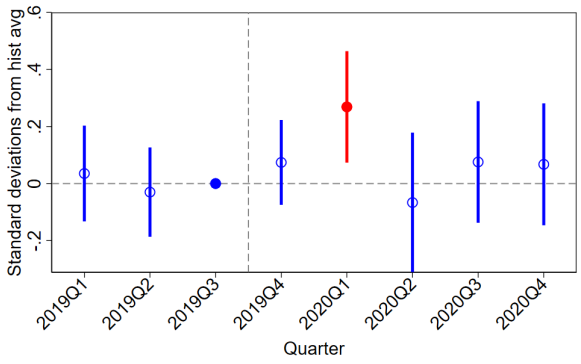
Table C.2: Joint tests on the coefficients for pre and past β_l.

Test Group	F-statistic	Degrees of Freedom	p-value
Pre Event Dummies	0.95	(2, 2395)	0.3867
Post Event Dummies	4.79	(5, 2395)	0.0002

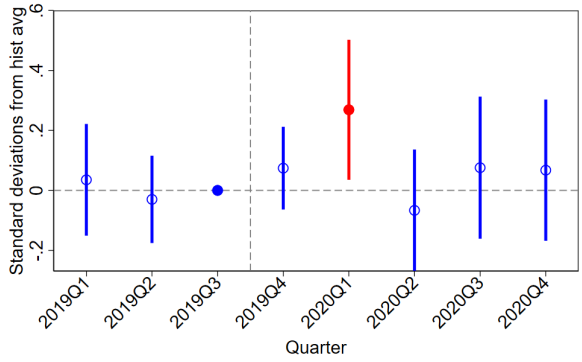
Notes: This table shows the joint tests on the coefficients for pre and past β_l from Equation C.1.



(A) Firm FE



(B) Firm FE and *Time* × *Sector* FE



(C) Cluster at the sector level

Figure C.4: Robustness Checks: China's COVID-19 Shutdown in 2020 Validation

Notes: This figure displays robustness checks for the validation at the firm level using the China COVID-19 shutdown event of 2020. Panel A adds firm fixed effects to Equation C.1. Panel B adds firm fixed effects and *Time* × *Sector* fixed effects to Equation C.1. Panel C clusters standard errors at the industry level. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals.

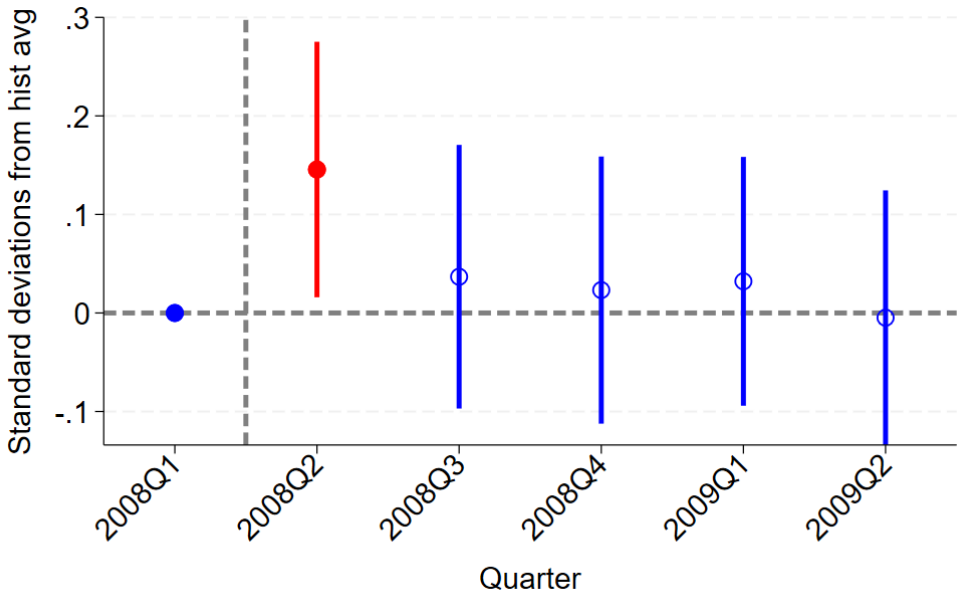


Figure C.5: Validation at the firm-level: Sichuan earthquake in 2008

Notes: This figure reports β_l coefficients from Equation C.1. The dummy *Treat* equals one if a firm imported inputs from China immediately before the Sichuan earthquake that occurred on May 12, 2008, and zero otherwise. The vertical line indicates the date of the eruption. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

C.2.2 Additional Validation Exercises

China earthquake in 2008: To further validate the FSCP indicator, I examine the supply chain pressures of firms directly exposed to the 2008 Sichuan earthquake in China. This earthquake, with a magnitude of 7.9 on the Richter scale, struck on May 12, 2008. If the FSCP accurately captures firm-level supply chain disruptions, firms with significant exposure to Chinese imports should experience elevated short-term supply chain pressures following the earthquake.

To define the treatment group I use the Hoberg and Moon (2017) offshore activities dataset to identify firms that import intermediate inputs from China at the moment of the Sichuan earthquake. Then, I run a similar difference-in-differences as in Equation C.1. Figure C.5 plots the β_l coefficients. In the quarter immediately following the event, firms in the treatment group experienced a supply chain pressure increase of 0.14 standard deviations more than those in the control group. This differential in supply chain pressure dissipates in the subsequent quarter as expected.

Eyjafjallajökull volcanic eruption in 2010: On April 14, 2010, the eruption of Eyjafjallajokull volcano in Iceland led to the disruption of some 100,000 flights in an interval of

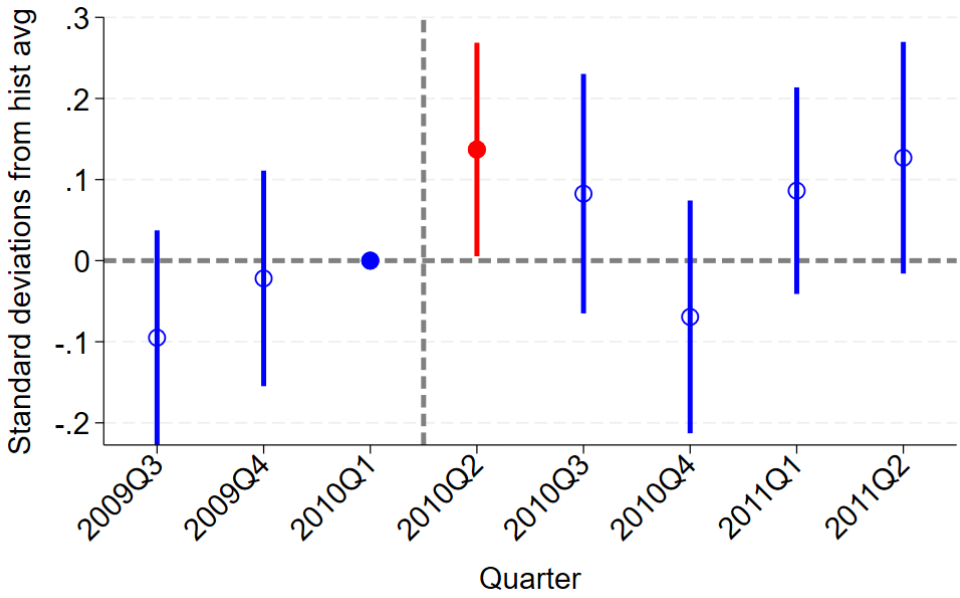


Figure C.6: Validation at the firm-level: Eyjafjallajökull volcanic eruption in 2010

Notes: This figure reports β_l coefficients of Equation C.1. The dummy *Treat* equals one if a firm imported any inputs immediately before the Eyjafjallajökull volcanic eruption on April 14, 2010, and zero otherwise. The vertical line indicates the date of the eruption. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

eight days according to Eurocontrol. Between April 15 and April 22 around 42% of cargo flights were canceled due to the volcano ash in European airspace; this percentage also includes overflights—flights neither departing from nor landing in Europe.[22]

As before, if the FSCP effectively captures firm-level supply chain disruptions, firms relying on imported inputs should exhibit unusual supply chain pressures following the volcanic eruption. While the event primarily impacted Europe, the ash cloud affected flights in several other countries as well. I define the treatment group as firms that reported importing inputs from any country immediately before the eruption of Eyjafjallajökull, and the control group as non-importing American firms. I run a similar difference-in-difference as in Equation C.1. Figure C.6 plots the β_l coefficients. Importers experienced an increase in supply chain pressures of 0.13 standard deviations more than firms in the control group in 2010Q2. When considering firms importing from Europe versus those importing from non-European countries, I do not find any differential effect.

[22]The complete Eurocontrol report is available at: https://www.eurocontrol.int/sites/default/files/article/attachments/20 ash-impact-on-traffic.pdf. Last accessed on November 10, 2024.

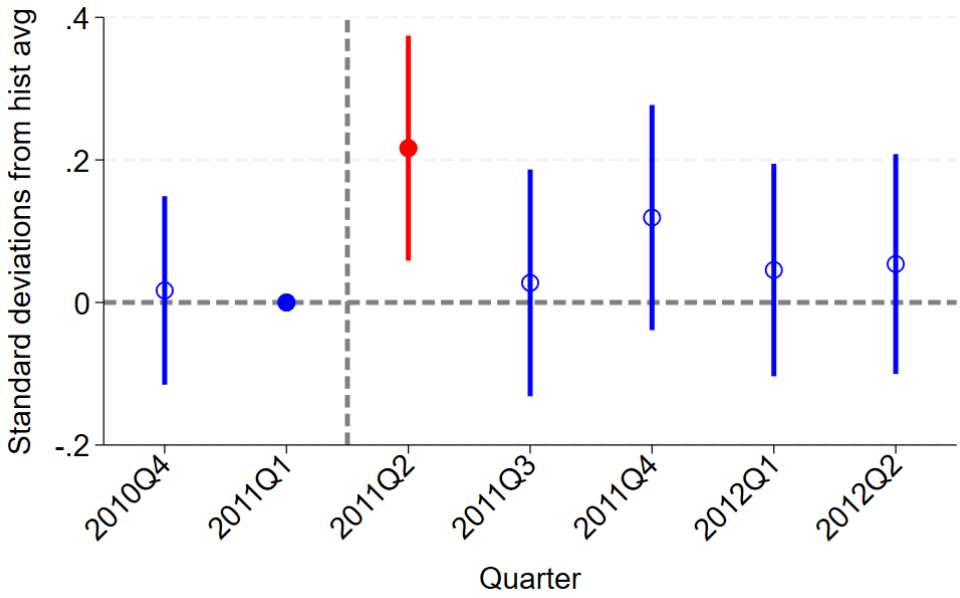


Figure C.7: Validation at the firm-level: Tōhoku earthquake

Notes: This figure reports β_l coefficients of Equation C.1. The dummy *Treat* equals one if a firm imported inputs from Japan immediately before the Tōhoku earthquake that occurred on March 11, 2011, and zero otherwise. The vertical line indicates the date of the Tōhoku earthquake. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

Tōhoku earthquake in Japan in 2011: This section exploits the Tōhoku earthquake that occurred on March 11, 2011. Boehm et al. (2019) shows that firms dependent on Japanese imports experienced a direct reduction in output proportional to the decline in imports after the Tōhoku earthquake up to four to six months after the event. As a result, American firms that imported intermediate goods from Japan should have experienced an increase in supply chain pressure compared to firms that did not import inputs from Japan. I use the Hoberg and Moon (2017) offshore activities dataset to identify firms that imported intermediate inputs from Japan at the moment of the Tōhoku earthquake. Firms mentioning buying inputs from Japan at the end of the 2010 fiscal year comprise the treatment group exposed to the earthquake, while firms that do not mention purchasing inputs from Japan comprise the control group not exposed to the natural disaster. Then, I run a similar difference-in-difference as in Equation C.1.

Figure C.7 plots the β_l coefficients. In the quarter immediately after the event, firms in the treatment group on average experienced an increase in unusual supply chain pressures equal to 0.22 standard deviations more than for in the control group, consistent with findings in the literature documenting that imports from Japan began to stabilize between four and six months after an initial post-earthquake disruption.

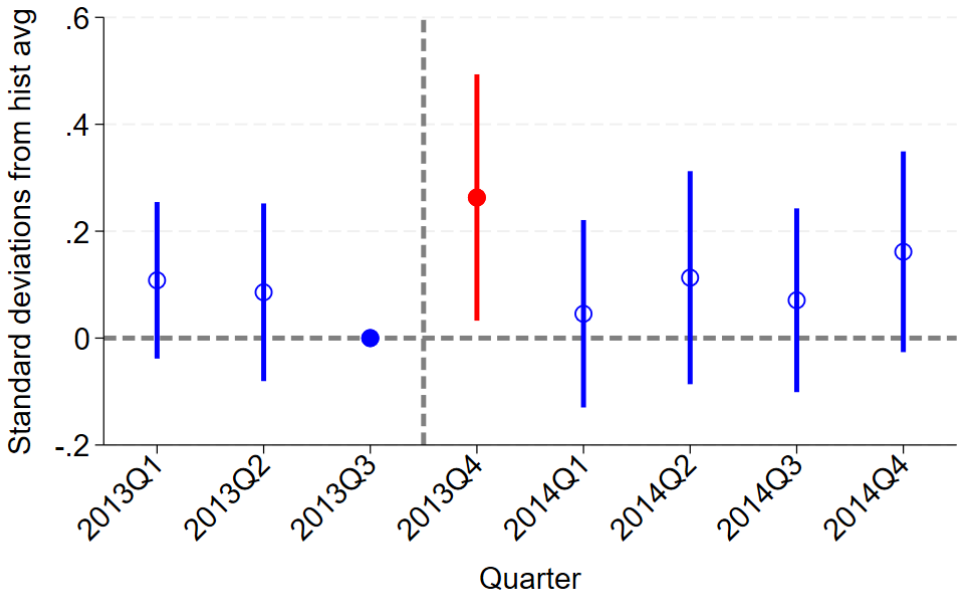


Figure C.8: Validation at the firm-level: Philippines Typhoon Haiyan 2013

Notes: This figure reports β_l coefficients of Equation C.1. The dummy *Treat* equals one if a firm imported inputs from the Philippines immediately before Typhoon Haiyan, which occurred in November 2013, and zero otherwise. The vertical line indicates the date of the natural disaster. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

Philippines Typhoon Haiyan 2013: Philippines was hit by Typhoon Haiyan in November 2013. The storm displaced more than 650,000 people and destroyed many of the residential and commercial buildings in Philippines. In this validation exercise, I use the Hoberg and Moon (2017) offshore activities dataset to identify firms that imported inputs from the Philippines right before the natural disaster occurred. Then, I run a similar difference-in-difference regression as in Equation C.1. Figure C.8 plots the β_l coefficients. Firms in the treatment group experienced an unusual supply chain pressure increase of 0.23 standard deviations more than those in the control group in the quarter of the shock.

Brazil truck drivers' strike in 2018: Another event study that created pressures on supply chains was the Brazilian truck drivers' strike. In protest against diesel prices, truck drivers started a strike on May 21, 2018, that lasted until May 30, 2018. The strike led to blockages on several key roads, disrupting the transportation of goods nationwide. The treatment consists of firms that imported inputs from Brazil just before the strike started. I run a similar difference-in-difference as in Equation C.1. Figure C.9 plots the β_l coefficients. Firms in the treatment group experienced an unusual supply chain pressure increase of 0.20 standard deviations more than those in the control group one quarter after the

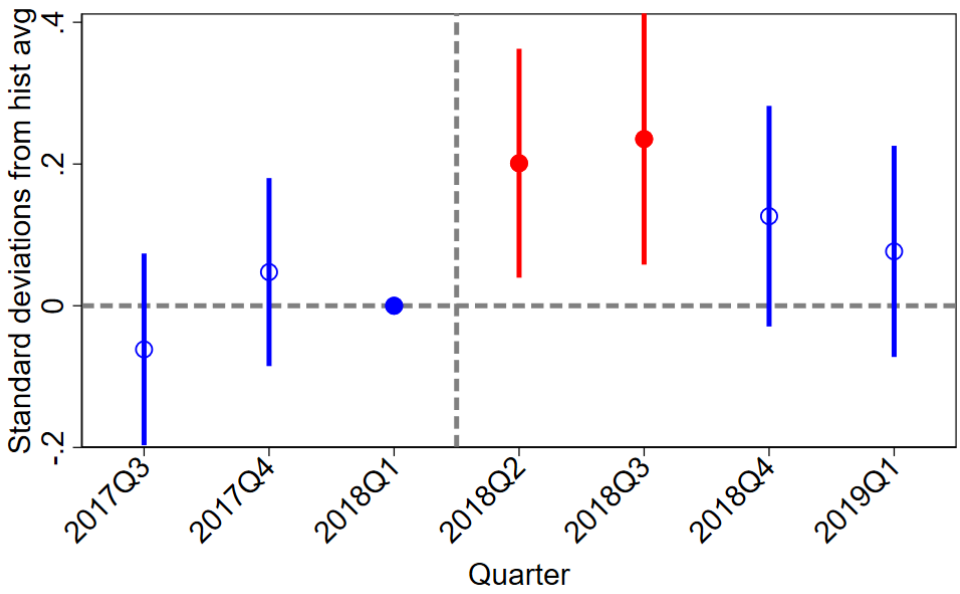


Figure C.9: Validation at the firm-level: Brazil truck drivers' strike

Notes: This figure reports β_l coefficients of Equation C.1. The dummy *Treat* equals one if the firms imported inputs from Brazil immediately before the Brazilian truck drivers' strike that occurred between May 21 and May 30, 2018, and zero otherwise. The vertical line indicates the date of the strike. The y-axis represents the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

beginning of the strike and it persisted in the following quarter.

Trade War between US and China (2018-2019): To validate the FSCP indicator's effectiveness in capturing firm-level supply chain disruptions, I focus on the first trade war between China and the United States between 2018 and 2019. A rapid escalation of tariffs and counter-tariffs characterized this period. The first tariff imposed exclusively on China under the Trump administration was announced in August of 2018 and started in September 2018 when the US imposed 10% tariffs on 200 billion USD of Chinese imports. These aggressive measures significantly pressured global supply chains. If the FSCP correctly captures firms' supply chain pressures, then firms relying on imported inputs from China should have experienced pronounced disruptions during the first U.S.–China trade war in 2018–2019. I therefore define the treatment group as firms that imported inputs from China immediately before the imposition of U.S. tariffs in September 2018, and the control group as firms not dependent on Chinese imports. Using the difference-in-differences framework of Equation C.1, Figure C.10 plots the estimated β_l coefficients. The results reveal that import-dependent firms experienced a statistically significant increase in supply chain pressures relative to the control group during the tariff escalation period.

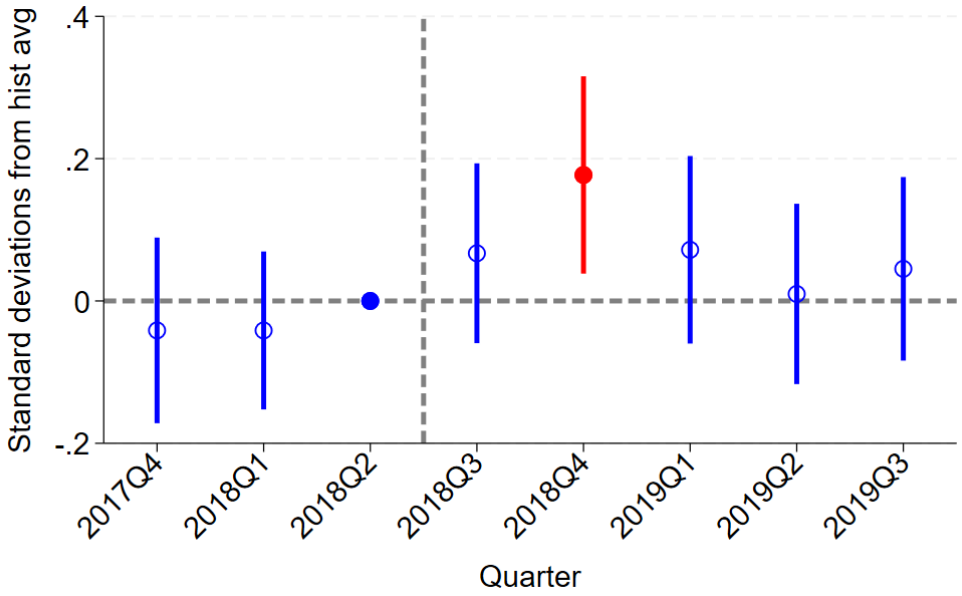


Figure C.10: Validation at the firm-level: Trade War between US and China (2018-2019)

Notes: This figure reports the β_l coefficients from Equation C.1. The dummy variable *Treat* equals one if a firms imported inputs from China immediately before the Trade War began in 2018Q3, and zero otherwise. The vertical line indicates the start of the 10% tariffs on 200 billion USD of Chinese imports. The y-axis shows the deviation from each firm's historical mean supply chain pressures, measured in standard deviations. Bands indicate 95% confidence intervals. Standard errors are clustered at the firm-level.

C.2.3 Descriptive Statistics

I characterize a "typical" supply chain-pressured firm. I classify firms as systematically pressured if their median raw FSCP over the entire sample exceeds the cross-sectional median All other firms are considered not to be systematically pressured. This classification relies solely on each firm's time series median, so the groupings remain consistent over time. Table C.3 displays the summary statistics for both groups, revealing clear contrasts in balance sheet profiles.

Table C.3: Descriptive Statistics of Firms Systematically Supply Chain-Pressured

	Not Systematically Pressured				**Systematically Pressured**			
Variable	Mean	SD	p25	p75	Mean	SD	p25	p75
Log Size	6.42	2.00	5.03	7.72	7.20	1.89	6.01	8.44
Log Capital	4.43	2.52	2.67	6.17	5.71	2.27	4.31	7.24
Capital / Assets	0.26	0.34	0.06	0.33	0.34	0.30	0.12	0.47
Inventories / Assets	0.05	0.09	0.00	0.05	0.15	0.13	0.05	0.21
Cash / Assets	0.28	0.27	0.06	0.44	0.16	0.18	0.03	0.21
Leverage	0.29	0.37	0.04	0.42	0.29	0.26	0.10	0.41
Sales Growth	0.02	0.25	–0.06	0.08	0.02	0.21	–0.06	0.09
Sales / Assets	0.20	0.17	0.09	0.27	0.28	0.20	0.15	0.36
COGS Growth	0.12	3.80	–0.05	0.09	0.04	1.18	–0.06	0.09
COGS / Assets	0.12	0.14	0.04	0.16	0.19	0.18	0.08	0.24
FSCP Raw ($\times$100)	0.08	0.38	0.00	0.01	0.51	1.05	0.01	0.51
Observations	63,274				78,903			

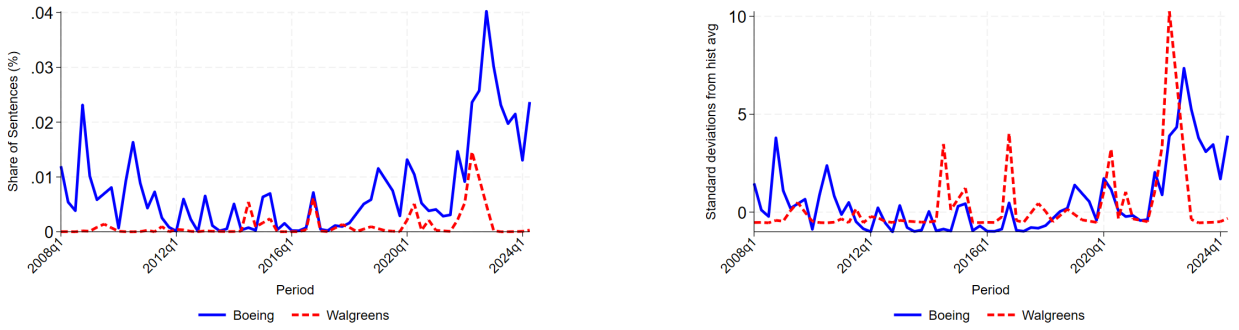
Notes: This table reports the summary statistics for firms not systematically supply chain-pressured versus firms systematically supply chain-pressure. Section 2 describes how the balance sheet variables are constructed. Section 3 details how the supply chain pressure indicator is constructed and which firms are considered systematically supply chain-pressured.

C.2.4 Aggregating sentences at the firm-level

Standardizing the FSCP indicator isolates unusual supply chain pressures specific to a firm from broader, systematic issues. By focusing on within-firm variation, the standardized FSCP indicator identifies whether a firm is experiencing pressure levels that deviate significantly from its historical norm and quantifies the magnitude of these deviations. For example, Figure C.11 compares the raw and standardized FSCP time series for Boeing and Walgreens.

In the raw FSCP, Boeing consistently shows a higher share of supply chain-related sentences, reflecting its inherently complex global supply chain network. However, the

standardized FSCP highlights that Walgreens experienced sharper peaks of abnormal pressures in 2022 compared to Boeing. This standardized approach offers a clearer perspective on deviations from each firm's typical levels, making it more effective for identifying genuinely abnormal supply chain disruptions.



(A) Raw FSCP (B) Standardized FSCP

Figure C.11: Comparison between raw and standardize FSCP indexes

Notes: This figure plots the supply chain pressure indicator time series for Boeing Company (sloid blue) and Walgreens Boots Alliance (dashed red). Panel A displays the raw FSCP indicator, which consists of the share of sentences related to supply chain pressures, while Panel B shows the standardized FSCP indicator, which consist of the standard deviation from the firm's historical mean (measured over the pre–supply-chain-crises period).

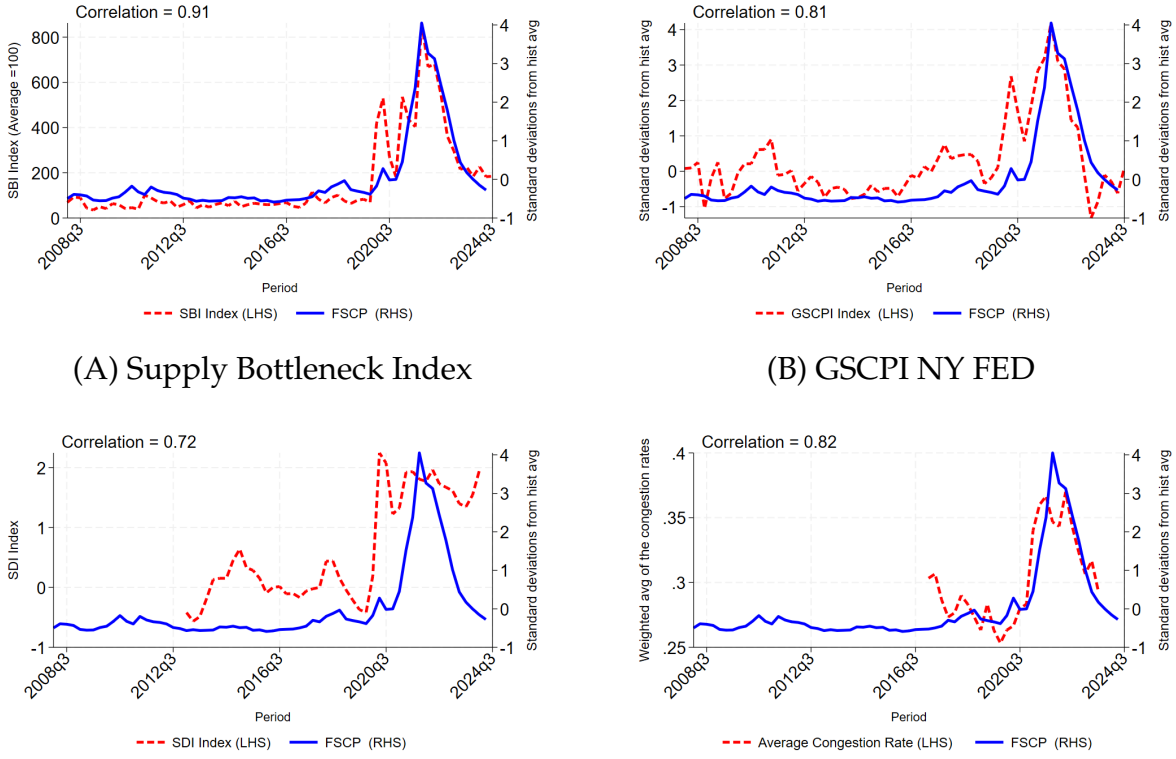
C.3 Agrgregate Level

Figure C.12 plots the average across firms of the overall FSCP index for the United States and compares it to popular indices of supply chain disruptions in the literature: the Global Supply Chain Pressure Index (GSCPI) from the Federal Reserve Bank of New York (Benigno et al., 2022), the Supply Bottleneck Index (SBI) from the Central Bank of Spain (Burriel et al., 2023), the Supply Disruptions Index (SDI) constructed by Liu et al. (2023), and the Average Congestion Rate (ACR) developed by Bai et al. (2024). The correlation with the SBI is 0.91, and with the GSCPI, it is 0.81. The lowest correlation is 0.72 with the SDI. These high correlations are reassuring because the series are constructed using very different data sources and methodologies, but nevertheless yield similar results.

Figure C.13 plots the discrete quarterly changes of GSCPI with FSCP. The correlation is equal to 0.59 for the full sample and it is equal to 0.72 from 2020Q1 onward. The high correlation using changes is reassuring that FSCP is capturing supply chain pressures at the aggregate level as well. Figure C.13 panel C also shows that the high correlation observed between the variable and GSCPI levels is robust and not solely influenced by the

post-pandemic period. Even when analyzing data from 2008Q1 to 2019Q4, prior to the COVID-19 pandemic, the correlation remains high at 0.63.

The FSCP index can be extended to other countries. Figure C.14 compares the FSCP with the SBI for China, France, Germany, Italy, Spain, and the United Kingdom. The correlations range between 0.84 and 0.93 for all countries.



(A) Supply Bottleneck Index

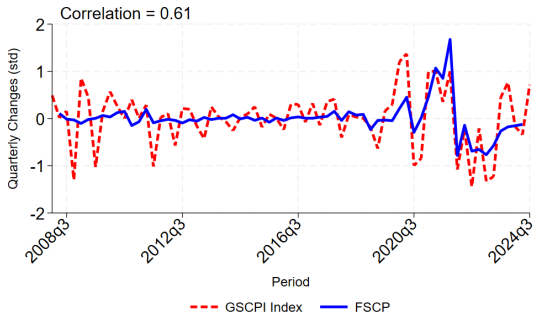
(B) GSCPI NY FED

(C) Supply Disruptions Index (SDI)

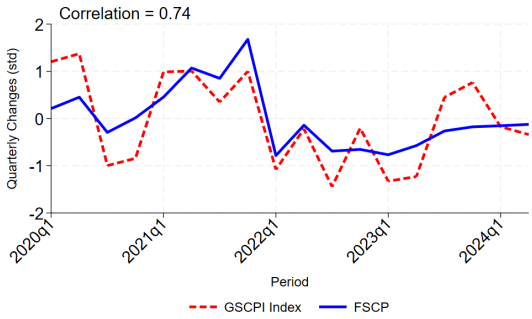
(D) Average Congestion Rate (ACR)

Figure C.12: Comparison across Supply Chain Pressure Indicators

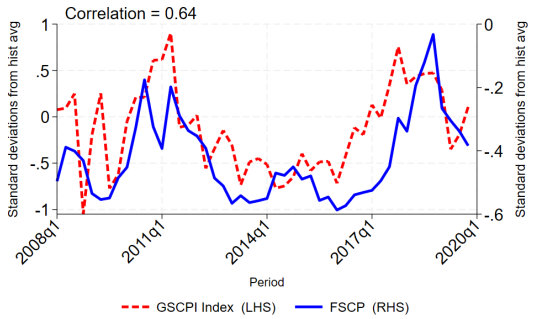
Notes: This figure plots the average FSCP index across firms (blue) for the United States and compares the FSCP to other popular supply chain disruption indices (red). Panel A: the Supply Bottleneck Index (SBI) from the Central Bank of Spain (Burriel et al., 2023); Panel B: the Global Supply Chain Pressure Index (GSCPI) from the Federal Reserve Bank of New York (Benigno et al., 2022); Panel C: the Supply Disruptions Index (SDI) constructed by Liu et al. (2023); Panel D: the Average Congestion Rate (ACR) developed by Bai et al. (2024). All time series are at a quarterly frequency, and the correlation between the FSCP and each alternative index appears in the top left of each panel.



(A) Quarterly Changes: All Sample



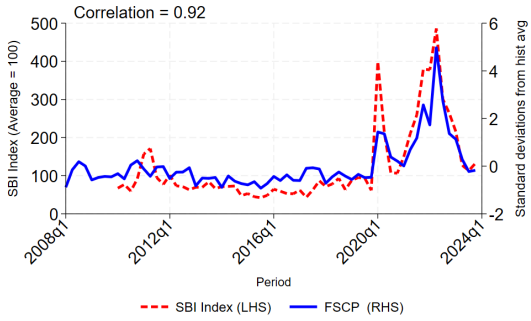
(B) Quarterly Changes: Post 2020



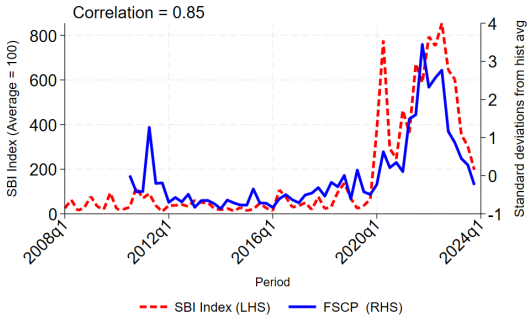
(C) Levels: 2008 - 2019 Sample

Figure C.13: FSCP vs GSCPI: Additional Validations

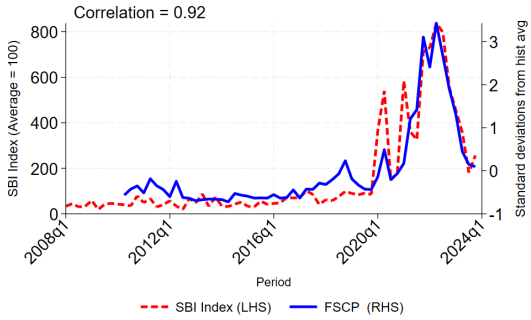
Notes: This figure compares quarter-over-quarter changes and levels of the Firm Supply Chain Pressure (FSCP) index across U.S. firms to the Global Supply Chain Pressure Index (GSCPI) from the Federal Reserve Bank of New York. Panel A plots the complete time series of quarter-over-quarter changes, spanning all available quarters. Panel B presents quarter-over-quarter changes from 2020Q1 to 2024Q3, highlighting the post-pandemic period. Panel C displays GSCPI levels for the pre-pandemic sample (2008Q1–2019Q4). All time series are presented at a quarterly frequency, with correlation values shown in the top left corner of each panel.



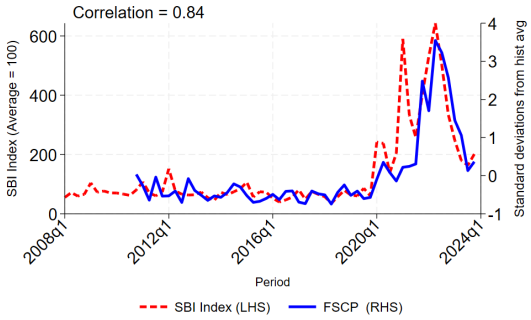
(A) China



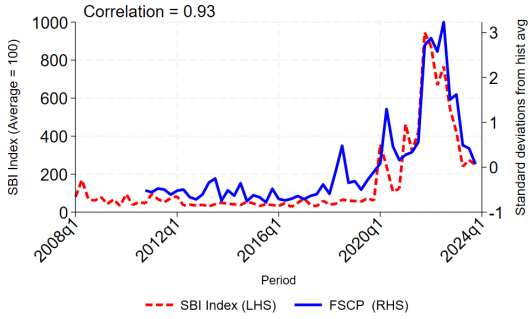
(B) France



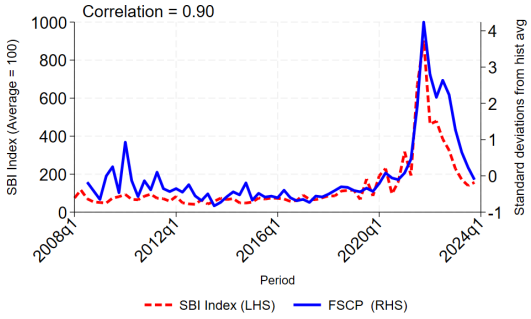
(C) Germany



(D) Italy



(E) Spain



(F) United Kingdom

Figure C.14: Cross-County Comparison with Supply Bottleneck Index

Notes: This figure plots the average FSCP index across firms (blue) at a quarterly frequency for six countries and compares it to the Supply Bottleneck Index (SBI) from the Central Bank of Spain (red), developed by Burriel et al. (2023) using text-based newspaper analysis. Panel A: China; Panel B: France; Panel C: Germany; Panel D: Italy; Panel E: Spain; Panel F: the United Kingdom. Correlation coefficients between the FSCP and SBI series appear in the top left corner of each panel.

D Additional Robustness and Results

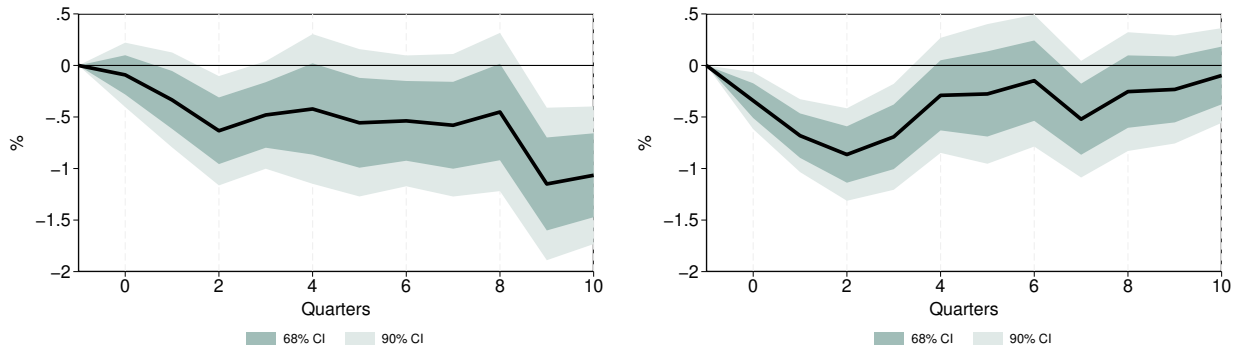
This section provides additional robustness and results for the empirical analysis. Appendix D.1 plots the additional results discussed on Section 4.1. D.2 estimates Equation 4.1 using alternative monetary policy shocks. Appendix D.3 shows the robustness to alternative supply chain pressures. Appendix D.4 revisits the inflation analysis using markup estimation. Finally, Appendix D.5 displays additional results related to Section 4.2.

D.1 Additional Results

Table D.1: Transition Matrix of Supply Chain Pressure States

	Period t		
Period $t-1$	Not Pressured	Pressured	Total
Not Pressured	79.06%	20.94%	100.00%
Pressured	39.64%	60.36%	100.00%
Total	65.57%	34.43%	100.00%

Notes: This table reports the transition matrix for firms' supply chain pressure states from period $t-1$ to period t. Pressure states are defined using the firm-level standardized FSCP. A firm is classified as "Pressured" in a given period if its standardized FSCP is above zero.



(A) Input-to-capital

(B) Input-to-sales

Figure D.1: The Effect of Monetary Policy on Firms' Input-to-Capital and Input-to-Sales Ratios: Supply Chain-Pressured vs. Non-Pressured

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in the cost-of-goods-sold-to-capital ratio (Panel A) and the cost-of-goods-sold-to-sales ratio (Panel B) in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on firms experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in the respective outcome variable.

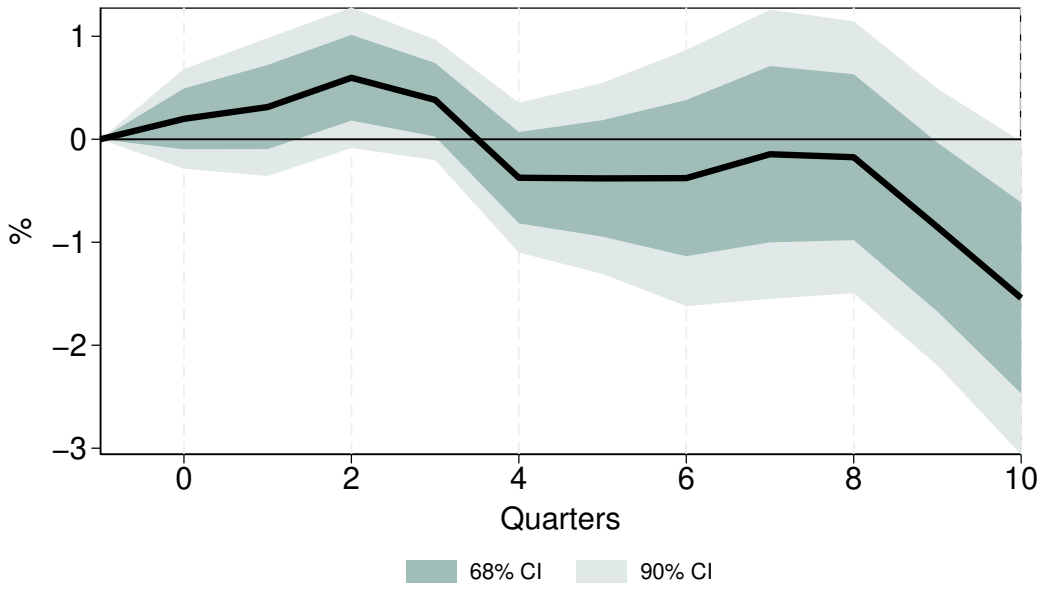
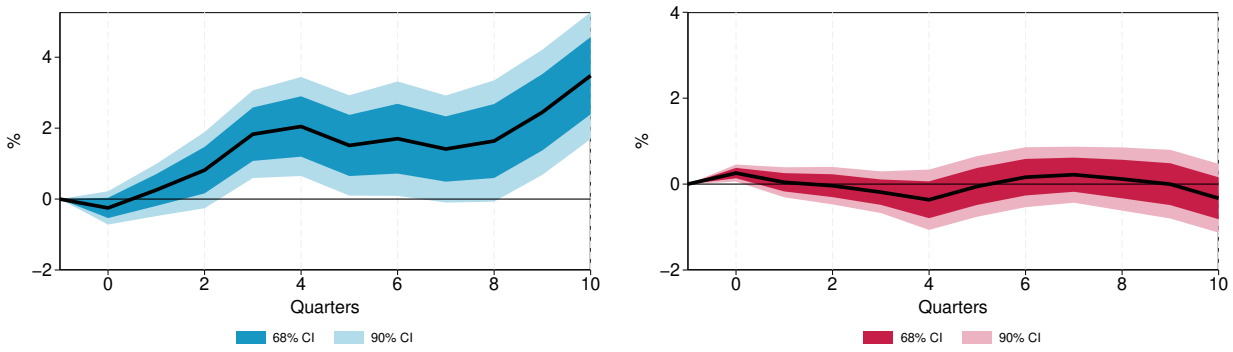


Figure D.2: The Effect of Monetary Policy on Firms' Intangible Investments: Supply Chain-Pressured vs. Non-Pressured

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in intangible capital investment in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on sectors experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in the outcome variable.

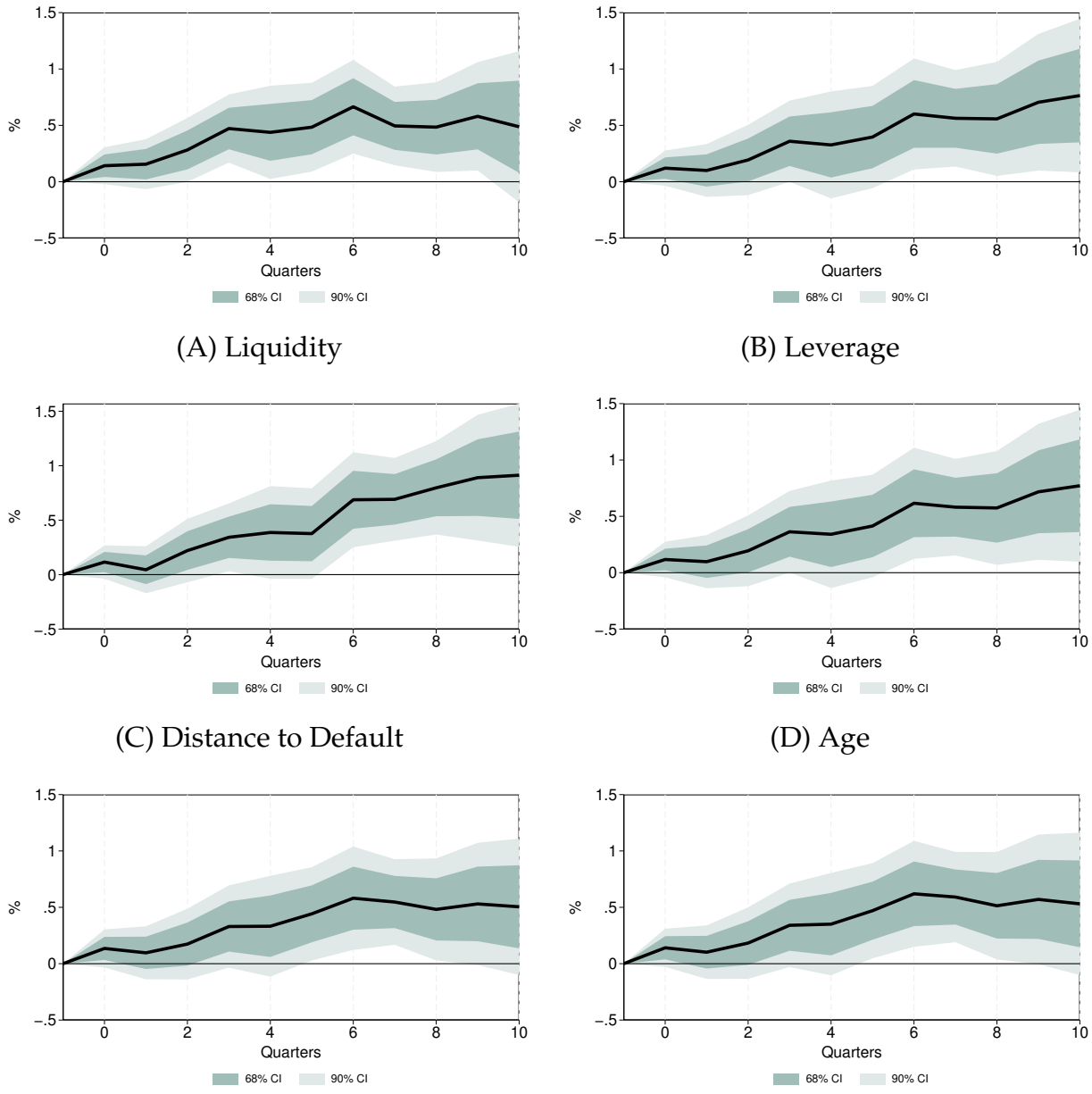


(A) Expansionary MPS

(B) Contractionary MPS

Figure D.3: The Asymmetric Effect of Monetary Policy on Firms' Investments: Supply Chain-Pressured vs. Non-Pressured

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in physical capital investment in response to a one standard deviation monetary policy shock. Panel A illustrates the effect of an expansionary shock (blue), and Panel B illustrates the effect of a contractionary shock (red), both estimated using Equation 4.2. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in physical capital investment.



(A) Liquidity

(B) Leverage

(C) Distance to Default

(D) Age

(E) Debt Constraint

(F) Equity Constraint

Figure D.4: Controlling for Financial Constraints

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in physical capital investment in response to a one standard deviation expansionary monetary policy shock, after controlling for various financial constraints interacted with the shock. It illustrates the additional effect of the shock on firms experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1. Panel A controls for liquidity (cash-to-assets); Panel B controls for leverage; Panel C controls for distance to default (Ottonello and Winberry, 2020); Panel D controls for firm age; Panel E controls for debt constraints; Panel F controls for equity constraints (Linn and Weagley, 2024). Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in physical capital investment.

D.2 Alternative Sample and Monetary Policy Shocks

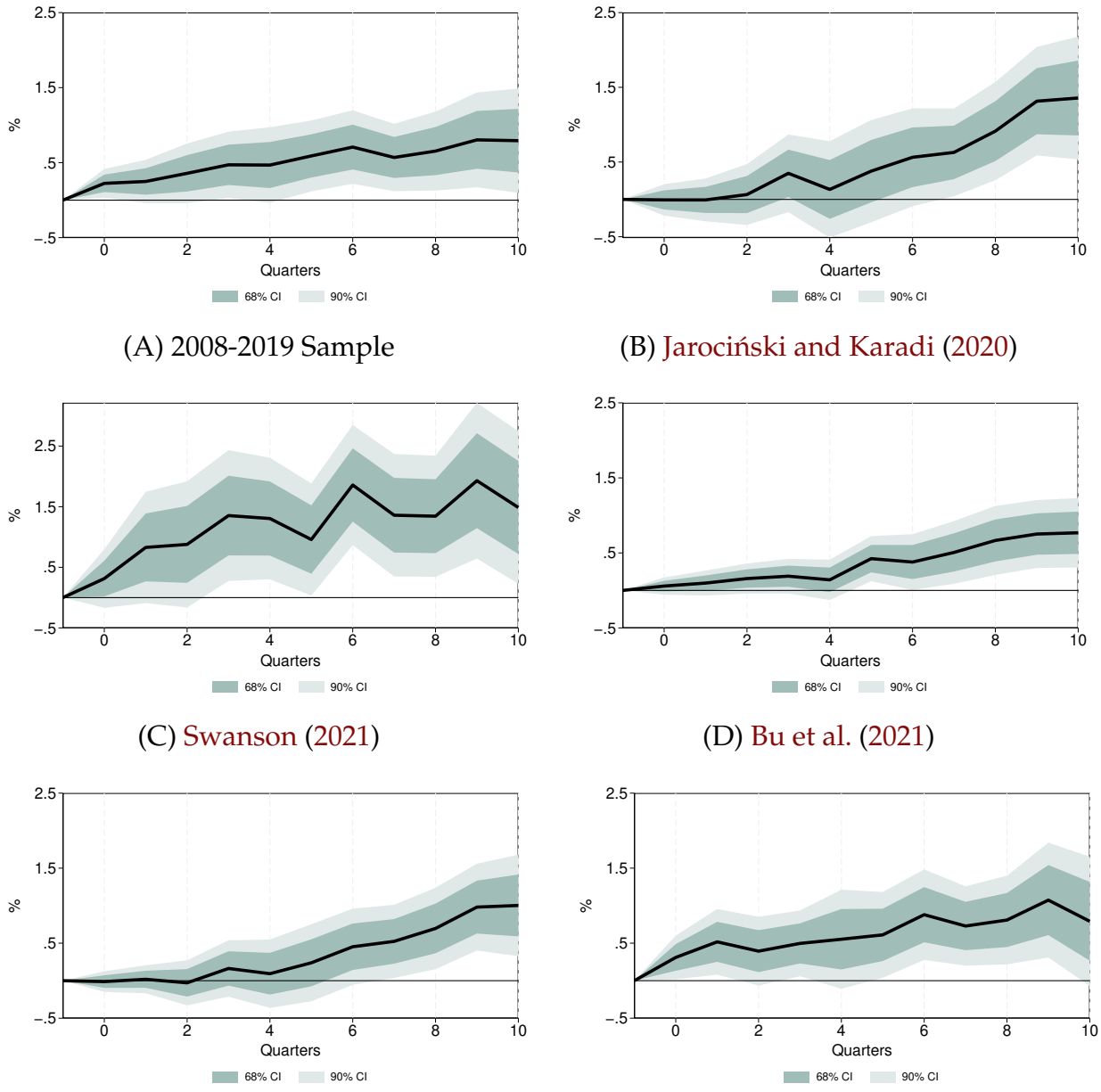
I confirm that the results remain robust to various U.S. monetary policy shocks. First, I restrict the sample to the period from the first quarter of 2008 (2008Q1) to the fourth quarter of 2019 (2019Q4) to ensure that the findings are not influenced by the post-COVID-19 era, which was marked by extreme supply chain pressures.

Then, I use the U.S. monetary policy shocks proposed by Jarociński and Karadi (2020), which disentangle monetary policy shocks from the central bank's assessment of the economic outlook. I then test the surprise changes in the federal funds rate constructed by Swanson (2021). This identification separately identifies the effects of unexpected rate changes, forward guidance, and large-scale asset purchases for each FOMC announcement. I also test for Bu et al. (2021) monetary policy shock series that uses Fama-MacBeth two-step procedure bridges periods of conventional and unconventional monetary policy in US. Finally, I employ both Gürkaynak et al. (2005), and Nakamura and Steinsson (2018) that are extended by Acosta (2022) until 2023Q4. Figures D.5 reports robustness results for physical capital investment across these alternative shock series.

D.3 Alternative Definitions of Firms Supply Chain-Pressured

In this section, I evaluate the robustness of the investment-response results by using different methods to define "supply chain pressured" firms. All specifications employ the baseline local projection framework from Equation 4.1, but they vary in how the binary treatment indicator is constructed.

Figure D.6 illustrates the results based on alternative classifications of supply chain pressured firms. In Panel A, a firm is classified as pressured if its raw FSCP score from $t-1$ falls within the top tercile of the distribution. Panel B uses the cross-sectional median as the cutoff point for classification. In Panel C, I set the threshold at zero, meaning that any firm with a positive raw FSCP is considered pressured. Finally, Panel D applies a continuous, standardized FSCP; I include both the standardized term and its square in the regression, with each term interacted with the monetary shock.



(A) 2008-2019 Sample

(B) Jarociński and Karadi (2020)

(C) Swanson (2021)

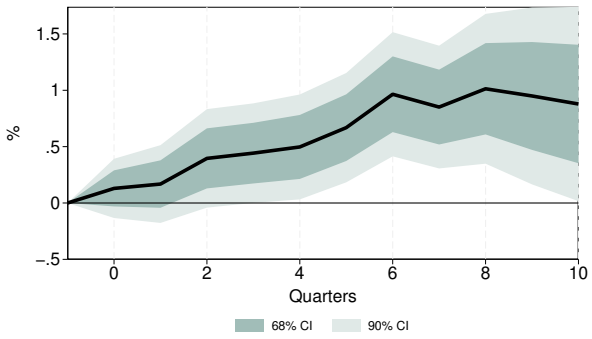
(D) Bu et al. (2021)

(E) Nakamura and Steinsson (2018)

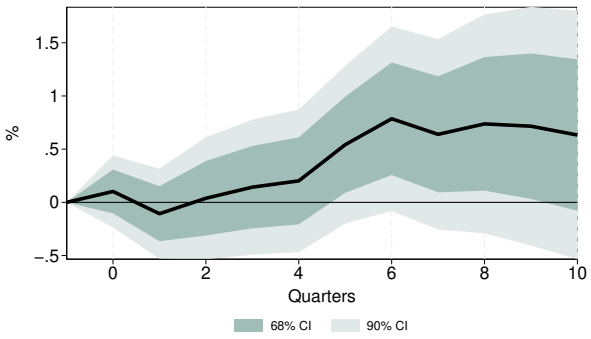
(F) Gürkaynak et al. (2005)

Figure D.5: The Effect of Monetary Policy on Firms' Physical Capital Investment: Robustness to Alternative Monetary Policy Shocks

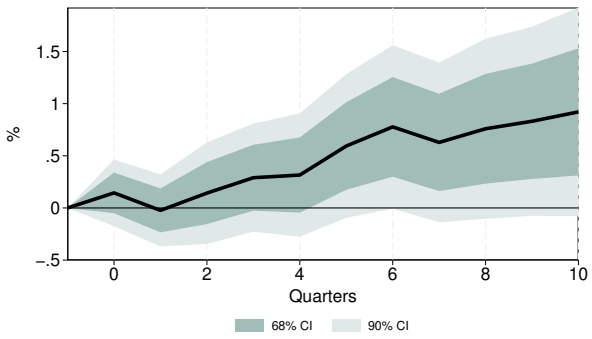
Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in physical capital investment in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on firms experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1. Panel A estimates the IRFs using the Bauer and Swanson (2023) shock series, restricted to the sample period 2008Q1–2019Q4. Panels B, C, D, E and F estimate the equation using the Jarociński and Karadi (2020), Swanson (2021), Bu et al. (2021), Nakamura and Steinsson (2018), and Gürkaynak et al. (2005) monetary policy shock series, respectively. Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in physical capital investment.



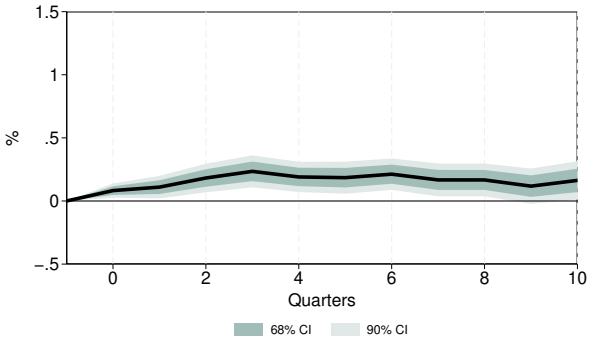
(A) Top Tercile



(B) Above Median



(C) Greater than Zero Raw FSCP



(D) Continuous FSCP (Standardized)

Figure D.6: Investment Dynamics: Alternative Definitions of Supply Chain-Pressured Firms

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in physical capital investment in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on firms experiencing supply chain pressures immediately before the shock, as estimated by Equation 4.1, but changing the definition of firms classified as supply chain pressured. Panel A considers firms whose raw FSCP score at $t-1$ is in the cross-sectional top tercile. Panel B classifies firms above the cross-sectional median of the raw FSCP at $t-1$. Panel C denotes firms with a raw FSCP score strictly greater than zero at $t-1$. Panel D used the continuous, standardized FSCP for each firm. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in physical capital investment.

D.4 Robustness Check: Markups

Markups are not directly observed. Thus, I use the Compustat North America Fundamentals Quarterly database to estimate markups via the production approach. The framework uses the firm's cost minimization method as proposed by Hall (1988). Recent papers (Loecker and Warzynski, 2012; De Loecker et al., 2020; Meier and Reinelt, 2022) show how to use the method to estimate firm-level markups with information from the firm's financial statements. The method relies on firm-level revenue and input expenditure data that are available on Compustat.

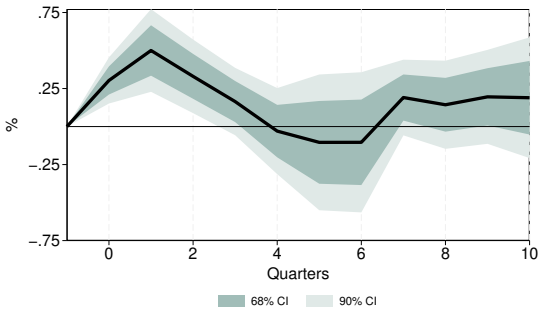
The markups are constructed by estimating sector-specific elasticities of output (*saleq*) to cost of goods sold (*cogs*), lumping together all firms that operate in a given sector as following:

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it}^{Q} Q_{it}}{P_{it}^{V} V_{it}}$$

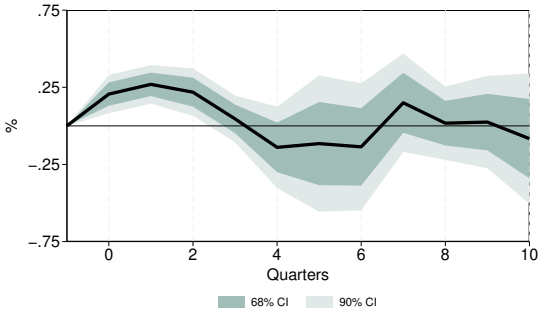
where θ_{it}^{V} is the output elasticity of a variable input, $P_{it}^{Q} Q_{it}$ is output (sales), and $P_{it}^{V} V_{it}$ is a variable input (cost of goods sold). As mentioned before, the output and the variable input are directly measurable, but the output elasticity needs to be estimated. I assume that firms in the same four-digit industry and quarter have a common output elasticity elasticity. I estimate time-varying elasticities by estimating production functions over twenty quarters of backward-looking rolling windows. This way, I can allow for changes in the production function parameters.

To test if a firm facing unusual supply chain pressure adjusts its price differently after an expansionary monetary policy shock, I use the equation 4.1 but substitute the outcome variable with the firm-level estimated markup. I also test the robustness of the results by considering different markup measures. First, I add selling, general, and administrative expenses (xsgaq) to the costs of goods sold. Second, I consider firms with at least 16 quarters of consecutive observations. Third, I keep firms with excessive real sales growth above 100% or below -67%. Fourth, I apply the accounting profit approach (Baqaee and Farhi, 2020). This markup measure uses operating income after depreciation, which is sales (saleq) minus costs of goods sold (cogsq), selling, general and administrative expenses (xsgaq), and depreciation and amortization (dpq). Finally, I estimate the baseline specification at the industry's NAICS 2 digit.

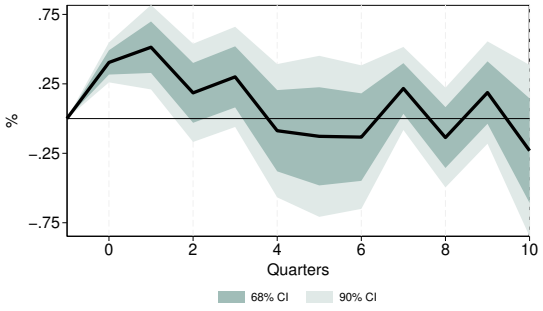
Figure D.7 exhibits the results from the empirical analysis using these alternative measures of markup.



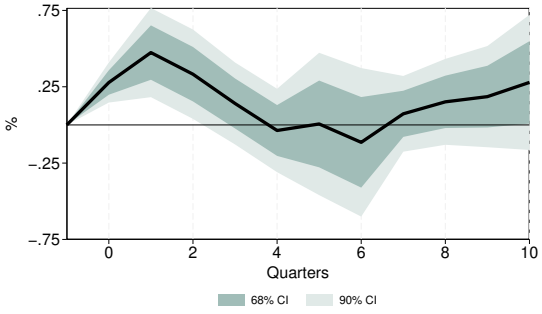
(A) Baseline



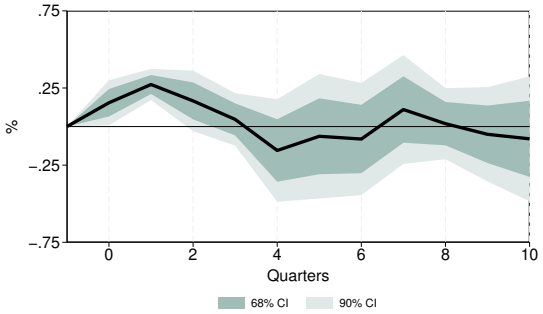
(B) Baseline incl. SGA



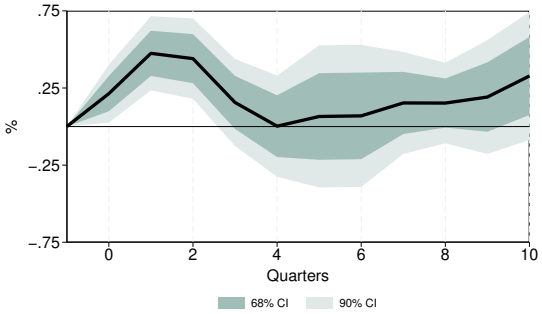
(C) Keep firms with excessive growth



(D) At least 16 quarters



(E) Accounting profit markups

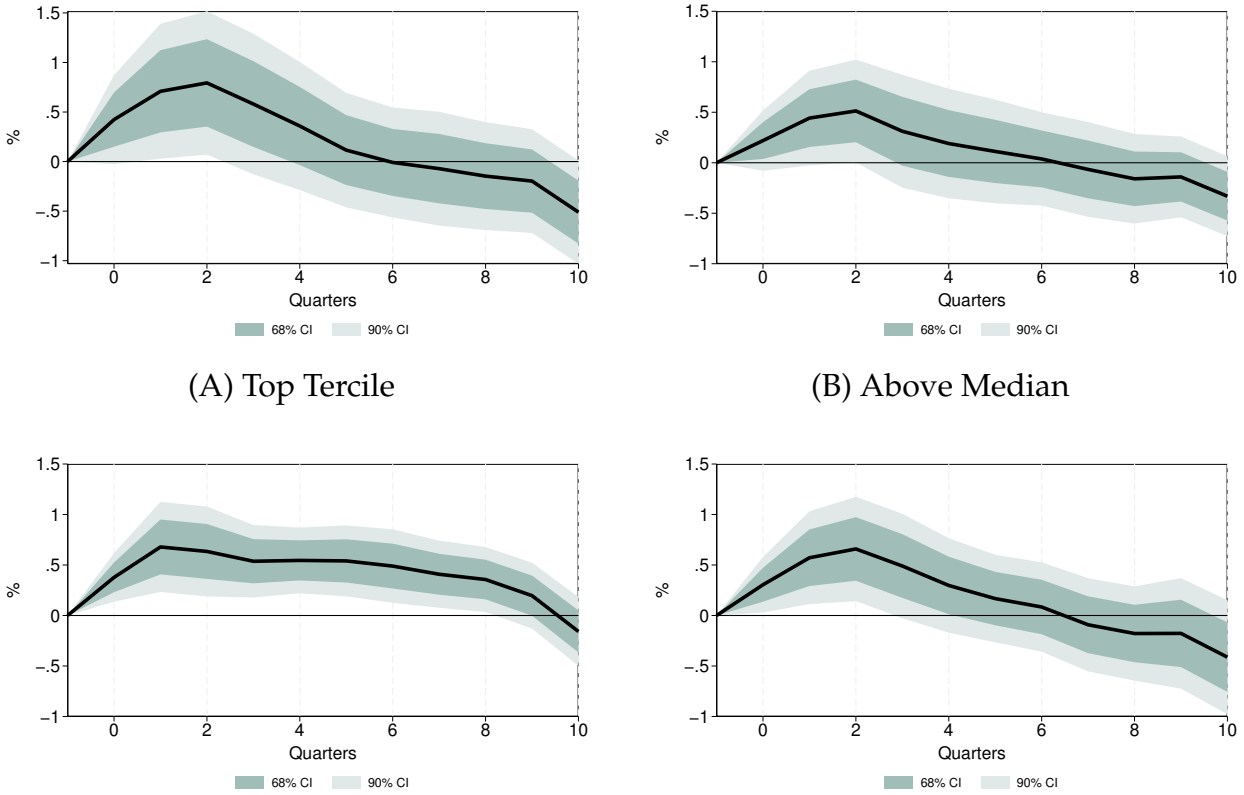


(F) Baseline - NAICS 2 Digit

Figure D.7: The Effect of Monetary Policy on Firms' Markup: Supply Chain-Pressured vs. Non-Pressured

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in markups in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on firms experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1 but cluster the standard error at NAICS 4-digit level since the firms elasticities are estimate at the sector level. Appendix D.4 details how each alternative markup measure is constructed. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the firm and time levels. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in markups.

D.5 Price Setting: Additional Results



(A) Top Tercile

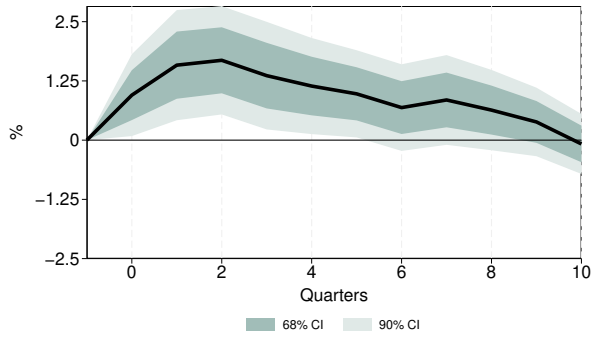
(B) Above Median

(C) Greater than Zero Raw FSCP

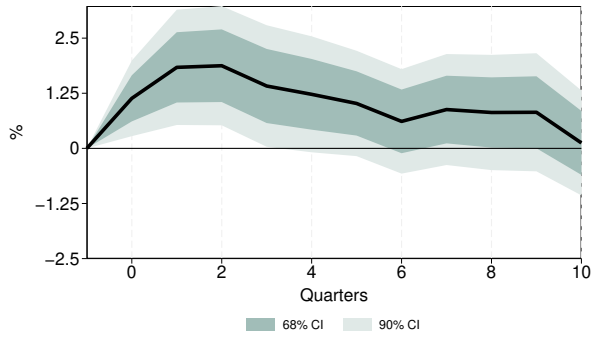
(D) Continuous FSCP (Standardized)

Figure D.8: Price Dynamics: Testing Different Definitions of Supply Chain Pressured Sectors

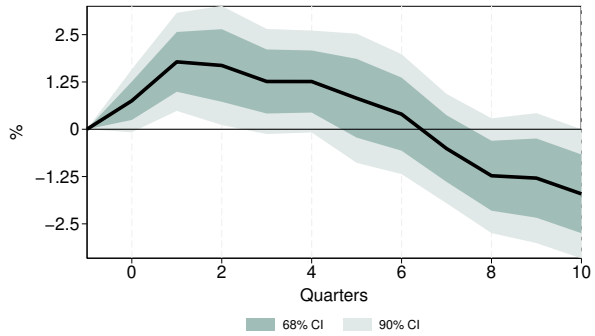
Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in in the Producer Price Index at NAICS-4 digit level in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on sectors experiencing supply chain pressures immediately before the shock, as estimated by Equation 4.3, but changing the definition of sectors classified as supply chain pressured. Panel A considers sectors whose raw FSCP score at $t-1$ is in the cross-sectional top tercile. Panel B classifies sectors above the cross-sectional median of the raw FSCP at $t-1$. Panel C denotes sectors with a raw FSCP score strictly greater than zero at $t-1$. Panel D used the continuous, standardized FSCP for each sectors. Monetary policy shocks are taken from Bauer and Swanson (2023). Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the sector level. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage changes in the PPI variable.



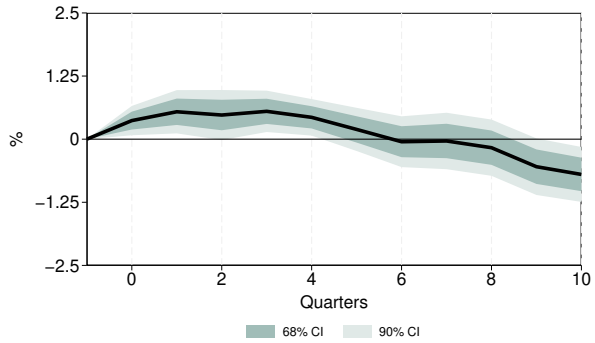
(A) 2008-2019 Sample



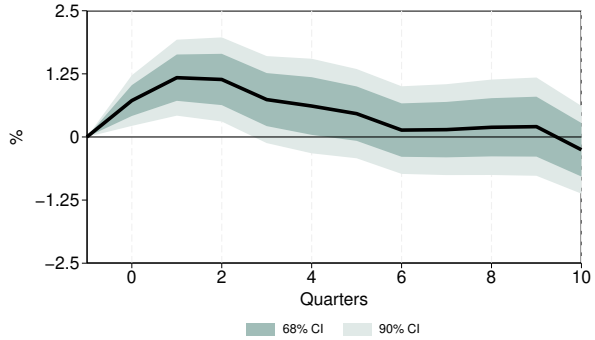
(B) Jarociński and Karadi (2020)



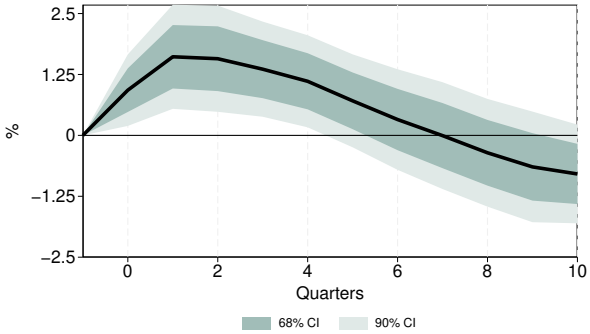
(C) Swanson (2021)



(D) Bu et al. (2021)



(E) Nakamura and Steinsson (2018)



(F) Gürkaynak et al. (2005)

Figure D.9: The Effect of Monetary Policy on Price Adjustments: Robustness to Alternative Monetary Policy Shocks

Notes: This figure shows the Impulse Response Functions (IRFs) for the cumulative percentage change in the Producer Price Index at NAICS-4 digit level in response to a one standard deviation expansionary monetary policy shock. It illustrates the additional effect of the shock on firms experiencing unusual supply chain pressures immediately before the shock, as estimated by Equation 4.1. Panel A estimates the IRFs using the Bauer and Swanson (2023) shock series, restricted to the sample period 2008Q1–2019Q4. Panels B, C, D, E and F estimate the equation using the Jarociński and Karadi (2020), Swanson (2021), Bu et al. (2021), Nakamura and Steinsson (2018), and Gürkaynak et al. (2005) monetary policy shock series, respectively. Shaded areas denote 68% and 90% confidence intervals, with standard errors clustered at the sector level. The horizontal axis measures quarters after the shock, and the vertical axis shows cumulative percentage change in the PPI variable.

E Full Model and Derivations

This section provides additional details regarding the model. Appendix E.1 outlines the household block. E.2 describes the four layers of the production side of the economy. Appendix E.3 presents the role of the central bank. E.4 specifies the market clearing conditions. Appendix E.5 details the model calibration process. Appendix E.6 derive the elasticity conditions. Finally, Appendix E.7 plots the impulse response function for an economy free from supply chain pressures.

E.1 Households

The economy is populated by a representative, infinitely lived household that derives utility from consumption C_t and suffers disutility from supplying hours L_t. The household discounts the future at the subjective factor $\beta \in (0,1)$ and has constant-relative-risk-aversion (CRRA) coefficient $\sigma > 0$. Labor supply elasticity is governed by $\chi > 0$, while $\psi > 0$ scales the disutility of work. Expected lifetime utility is

$$\max_{\{C_t, L_t, B_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma} - 1}{1-\sigma} - \frac{\psi L_t^{1+\chi}}{1+\chi} \right]. \tag{HH-1}$$

Nominal budget constraint. Each period the household allocates resources between consumption and purchases of one-period nominal bonds B_t (in zero-coupon units) that pay the gross nominal return $1 + i_t$ next period. Its nominal flow-of-funds constraint is

$$P_t C_t + B_t = W_t L_t + (1 + i_{t-1}) B_{t-1} + DIV_t, \tag{HH-2}$$

where P_t is the aggregate price level, W_t the nominal wage, and DIV_t aggregate cash flows distributed by firms.

Real variables. Dividing (HH-2) by P_t and defining real variables

$$\pi_t \equiv \frac{P_t}{P_{t-1}}, \qquad w_t \equiv \frac{W_t}{P_t}, \qquad b_t \equiv \frac{B_t}{P_t}, \qquad div_t \equiv \frac{DIV_t}{P_t},$$

gives the real budget constraint

$$C_t + b_t = w_t L_t + (1 + i_{t-1}) \frac{b_{t-1}}{\pi_t} + div_t. \tag{HH-3}$$

First-order conditions

1. **Intratemporal (labor–leisure) choice**

$$w_t C_t^{-\sigma} = \psi L_t^{\chi} \tag{HH-4}$$

2. **Intertemporal (Euler) condition for bonds**

$$\lambda_t = \beta E_t[\lambda_{t+1}(1+i_t)/\pi_{t+1}]\,. \tag{HH-5}$$

   Using $\lambda_t = C_t^{-\sigma}$ from the marginal utility of consumption, the Euler equation becomes

$$1 = \beta(1+i_t)E_t\left[\left(\frac{C_t}{C_{t+1}}\right)^{\sigma}\frac{1}{\pi_{t+1}}\right] \tag{HH-6}$$

3. **Stochastic discount factor.** Collecting the terms that price one unit of real consumption tomorrow in units of real consumption today yields

$$\Lambda_{t,t+1} \;\equiv\; \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}\frac{1}{\pi_{t+1}} \tag{HH-7}$$

E.2 Production

There are several layers on the production side of the economy. A representative wholesale firm transforms capital and intermediate inputs into output, $Y_{m,t}$. New intermediate inputs, M_t, are produced by a competitive intermediate-goods sector using labor L_t in a linear technology. Wholesale output is sold to a continuum of retail firms indexed by $f \in [0,1]$. Each retail firm simply repackages wholesale output via

$$Y_t(f) \;=\; Y_{m,t}(f),$$

and then sells its output to a competitive final-goods firm. The final output good, Y_t, is a CES aggregate of retail outputs with elasticity of substitution $\epsilon_p > 1$. Retailers thus face the demand curve

$$Y_t(f) \;=\; \left(\frac{P_t(f)}{P_t}\right)^{-\epsilon_p} Y_t, \tag{R.1}$$

where $P_t(f)$ is the price set by retailer f. The aggregate price index P_t then satisfies

$$P_t^{1-\epsilon_p} \;=\; \int_0^1 P_t(f)^{\,1-\epsilon_p}\, df. \tag{R.2}$$

E.2.1 Retailers

The nominal profit of retail firm f is

$$\text{DIV}_{R,t}(f) \;=\; P_t(f)\, Y_t(f) \;-\; P_{m,t}\, Y_{m,t}(f).$$

Equating $Y_{m,t}(f) \;=\; Y_t(f)$ with the demand function (R.1), we obtain the retailer's nominal profit:

$$\text{DIV}_t^R(f) = P_t(f)^{1-\epsilon_p}\, P_t^{\epsilon_p}\, Y_t \;-\; P_{m,t}\; P_t(f)^{-\epsilon_p}\, P_t^{\epsilon_p}\, Y_t. \tag{R.3}$$

Each period, a retailer can reset its price with probability $1-\phi_p$. If it sets $P_t(f)$ in period t, that price remains in effect in $t+j$ with probability ϕ_p^j, and is indexed to past inflation by γ_p. An unadjusted price in period $t+j$ thus becomes

$$P_t(f)\left(\tfrac{P_{t+j-1}}{P_{t-1}}\right)^{\gamma_p}.$$

When each firm re-optimize in t, the retailer chooses $P_t(f)$ to

$$\max_{P_t(f)}\; E_t \sum_{j=0}^{\infty} \phi_p^j\, \Lambda_{t,t+j} \Bigg[P_t(f)^{1-\epsilon_p} \left(\tfrac{P_{t+j-1}}{P_{t-1}}\right)^{(1-\epsilon_p)\gamma_p} P_{t+j}^{\epsilon_p-1} Y_{t+j} \\ -\; P_{m,t+j}\, P_t(f)^{-\epsilon_p} \left(\tfrac{P_{t+j-1}}{P_{t-1}}\right)^{-\epsilon_p\gamma_p} P_{t+j}^{\epsilon_p-1} Y_{t+j} \Bigg].$$

The first-order condition with respect to $P_t(f)$ is

$$(\epsilon_p - 1)\, P_t(f)^{-\epsilon_p}\, E_t \sum_{j=0}^{\infty} \phi_p^j\, \Lambda_{t,t+j} \left(\tfrac{P_{t+j-1}}{P_{t-1}}\right)^{(1-\epsilon_p)\gamma_p} P_{t+j}^{\epsilon_p-1} Y_{t+j} \;=$$

$$\epsilon_p \, P_t(f)^{-\epsilon_p - 1} \, E_t \sum_{j=0}^{\infty} \phi_p^j \, \Lambda_{t,t+j} \, P_{m,t+j} \left(\frac{P_{t+j-1}}{P_{t-1}} \right)^{-\epsilon_p \gamma_p} P_{t+j}^{\epsilon_p} Y_{t+j}.$$

Define the following auxiliary variables:

$$X_{1,t} = \sum_{j=0}^{\infty} (\phi_p \beta)^j \frac{\mu_{t+j}}{\mu_t} \, P_{m,t+j} \Big(\frac{P_{t+j-1}}{P_{t-1}} \Big)^{-\epsilon_p \gamma_p} P_{t+j}^{\epsilon_p} \, Y_{t+j}, \tag{R.4}$$

$$X_{2,t} = \sum_{j=0}^{\infty} (\phi_p \beta)^j \frac{\mu_{t+j}}{\mu_t} \Big(\frac{P_{t+j-1}}{P_{t-1}} \Big)^{(1-\epsilon_p)\gamma_p} P_{t+j}^{\epsilon_p - 1} \, Y_{t+j}. \tag{R.5}$$

All retailers reset to the same optimal price P_t^*. The first-order condition for price setting then yields

$$P_t^* \;=\; \frac{\epsilon_p}{\epsilon_p - 1} \, \frac{X_{1,t}}{X_{2,t}}. \tag{R.6}$$

Finally, define the scaled variables

$$x_{1,t} = \frac{X_{1,t}}{P_t^{\epsilon_p}}, \quad x_{2,t} = \frac{X_{2,t}}{P_t^{\epsilon_p - 1}}, \quad p_t^* = \frac{P_t^*}{P_t}.$$

In these terms, the recursions become

$$x_{1,t} = p_{m,t} \, Y_t \;+\; \phi_p \, E_t \left[\Lambda_{t,t+1} \left(\frac{\Pi_{t+1}}{\Pi_t^{\gamma_p}} \right)^{\epsilon_p} x_{1,t+1} \right],$$

$$x_{2,t} = Y_t \;+\; \phi_p \, E_t \left[\Lambda_{t,t+1} \left(\frac{\Pi_{t+1}}{\Pi_t^{\gamma_p}} \right)^{\epsilon_p - 1} x_{2,t+1} \right].$$

and the reset-price rule is

$$p_t^* \;=\; \frac{\epsilon_p}{\epsilon_p - 1} \, \frac{x_{1,t}}{x_{2,t}}. \tag{E.1}$$

E.2.2 Aggregation

Integrating the demand for retail output (R.1) across all retailers, and using $Y_t(f) = Y_{m,t}(f)$ with $\int_0^1 Y_{m,t}(f) \, df = Y_{m,t}$, results in the condition:

$$Y_t \, v_t^p \;=\; Y_{m,t}, \tag{A.1}$$

where the price-dispersion index v_t^p is defined as

$$v_t^p \;=\; \int_0^1 \Big(\frac{P_t(f)}{P_t} \Big)^{-\epsilon_p} df.$$

Using the properties of Calvo pricing with indexation to lagged inflation, one shows

$$\begin{aligned} v_t^p &= (1-\phi_p)\,(p_t^*)^{-\epsilon_p} \;+\; \int_{1-\phi_p}^{1} \left(\frac{\Pi_{t-1}^{\gamma_p}\, P_{t-1}(f)}{P_t}\right)^{-\epsilon_p} df \\ &= (1-\phi_p)\,(p_t^*)^{-\epsilon_p} \;+\; \Pi_{t-1}^{-\gamma_p\epsilon_p}\, P_t^{\epsilon_p}\, P_{t-1}^{-\epsilon_p} \int_{1-\phi_p}^{1} \left(\frac{P_{t-1}(f)}{P_{t-1}}\right)^{-\epsilon_p} df. \end{aligned} \tag{E.2}$$

By a law of large numbers this reduces to

$$v_t^p \;=\; (1-\phi_p)\,(p_t^*)^{-\epsilon_p} \;+\; \phi_p \left(\frac{\Pi_t}{\Pi_{t-1}^{\gamma_p}}\right)^{\epsilon_p} v_{t-1}^p. \tag{A.2}$$

Similarly, using (R.2), the aggregate price index can be written as

$$\begin{aligned} P_t^{\,1-\epsilon_p} &= (1-\phi_p)\,(P_t^*)^{\,1-\epsilon_p} \;+\; \int_{1-\phi_p}^{1} \Pi_{t-1}^{\gamma_p\,(1-\epsilon_p)}\, P_{t-1}(f)^{\,1-\epsilon_p}\, df \\ &= (1-\phi_p)\,(P_t^*)^{\,1-\epsilon_p} \;+\; \phi_p\, \Pi_{t-1}^{\gamma_p\,(1-\epsilon_p)}\, P_{t-1}^{\,1-\epsilon_p}. \end{aligned}$$

Dividing both sides by $P_t^{\,1-\epsilon_p}$ gives

$$1 \;=\; (1-\phi_p)\,(p_t^*)^{\,1-\epsilon_p} \;+\; \phi_p\, \Pi_{t-1}^{\gamma_p\,(1-\epsilon_p)}\, \Pi_t^{\epsilon_p-1}. \tag{A.3}$$

E.3 Monetary Policy

The central bank sets the nominal interest rate according to a Taylor rule:

$$i_t \;=\; i_{ss} \;+\; \phi_\pi \ln\!\left(\frac{\Pi_t}{\Pi}\right) \;+\; \phi_y\,(Y_t - Y_{t-1}) \;+\; s_m \varepsilon_t^m \tag{E.3}$$

where

$$\Pi_t = \frac{P_t}{P_{t-1}},$$

and Π denotes the steady-state inflation rate.

E.4 Market Clearing Conditions

Goods Market Aggregate output must equal the sum of consumption and investment:

$$Y_t \;=\; C_t \;+\; I_t$$

Bond Market Bonds are assumed to be in zero net supply:

$$b_t = 0$$

E.5 Calibration

Table E.1 reports the calibration of the key parameters, most of which follow standard values in the literature (e.g., Sims and Wu (2021); Sims et al. (2023)). Time is measured quarterly. I set $\beta = 0.995, \delta = 0.025$ for the discount factor and the steady-state depreciation rate on capital. The inverse Frisch elasticity of labor supply is $\chi = 1$. The disutility-of-labor scaling parameter ψ is calibrated so that steady-state labor input equals unity. In the production function, capital's share is set to $\alpha = 0.33$. Price rigidities, ϕ_p imply average durations of one year, and I rule out backward indexation by setting $\gamma_p = 0$ Finally, the Taylor rule ϕ_π, ϕ_y are standard.

Table E.1: Calibrated Parameters

Parameter	Value or Target	Description
β	0.995	Discount factor
χ	1	Inverse Frisch elasticity
ψ	$L = 1$	Labor disutility scaling parameter / steady state labor
α	0.33	Production function exponent on capital
δ	0.025	Steady state depreciation
Π	1	Steady state (gross) inflation
ϵ_p	11	Elasticity of substitution goods
ϕ_p	0.75	Price rigidity
γ_p	0	Price indexation
ϕ_π	1.5	Taylor rule inflation
ϕ_y	0.25	Taylor rule output growth
s_m	0.0025	SD monetary policy shock

Note: This table lists the values of calibrated parameters or the target used in the calibration. They follow follow standard values in the literature (Sims and Wu (2021); Sims et al. (2023)).

E.6 Elasticity Conditions Under Supply Chain Pressures

E.6.1 Input–Price Response

Starting from first order condition for intermediate orders and solving for $p_{m,t}$:

$$p_{m,t}(1-\alpha)K_t^\alpha \, \Phi_M(M_t, S) \, \Phi(M_t, S)^{-\alpha} = p_t^M,$$

$$p_{m,t} = C_t \, \frac{\Phi(M_t, S)^{\alpha}}{\Phi_M(M_t, S)}, \tag{E.1}$$

where $C_t \equiv \frac{p_t^M}{(1-\alpha)K_t^{\alpha}}$. Taking logs of (E.1) and differentiating with respect to M_t gives

$$A(M_t, S) \equiv \frac{\partial \ln p_{m,t}}{\partial M_t} = \alpha \, \frac{\Phi_M}{\Phi} - \frac{\Phi_{MM}}{\Phi_M}. \tag{E.2}$$

The sensitivity of the input's elasticity with respect to supply chain pressure. We can differentiate (E.2) with respect to S:

$$\frac{\partial A}{\partial S} = \alpha \frac{\Phi_{MS}}{\Phi} - \alpha \frac{\Phi_M \Phi_S}{\Phi^2} - \frac{\Phi_{MMS}}{\Phi_M} + \frac{\Phi_{MM}\,\Phi_{MS}}{\Phi_M^2}. \tag{E.3}$$

Under the function $\Phi(M_t, S)$ conditions stated in Section 5: (i) $\Phi_M > 0$, $\Phi_M \leq 1$,(ii) $\Phi_S < 0$, (iii) $\Phi_{MS} \leq 0$, (iv) $\Phi_{MM} \leq 0$, (v) $\Phi_{MMS} \leq 0$, it follows that

(a) $\alpha \dfrac{\Phi_{MS}}{\Phi} \leq 0$

(b) $-\alpha \dfrac{\Phi_M \Phi_S}{\Phi^2} \geq 0$

(c) $-\dfrac{\Phi_{MMS}}{\Phi_M} \geq 0$

(d) $\dfrac{\Phi_{MM}\Phi_{MS}}{\Phi_M^2} \geq 0$

Terms (b), (c), and (d) are therefore non-negative, term (a) is non-positive. It is convenient to write Equation (E.3) as

$$\frac{\partial A}{\partial S} = \alpha \left(\frac{\Phi_{MS}}{\Phi} - \frac{\Phi_M \Phi_S}{\Phi^2} \right) - \frac{\Phi_{MMS}}{\Phi_M} + \frac{\Phi_{MM}\Phi_{MS}}{\Phi_M^2}.$$

The term in parenthesis becomes

$$\alpha \left(\frac{\Phi_{MS}}{\Phi} - \frac{\Phi_M \Phi_S}{\Phi^2} \right) = \frac{\alpha}{\Phi^2} \left[\, \Phi \, \Phi_{MS} - \Phi_M \Phi_S \right].$$

Recall the last condition introduced in Section 5

$$\Phi_M(-\Phi_S) \;\geq\; \Phi(-\Phi_{MS}) \quad \Longrightarrow \quad \Phi \, \Phi_{MS} - \Phi_M \Phi_S \;\geq\; 0,$$

Therefore, the entire expression is non–negative, confirming that

$$\frac{\partial A}{\partial S} \;\geq\; 0, \quad \text{strict if } S > 0$$

Next, define the semi-elasticity of input orders to the wholesale price:

$$\varepsilon_{M,p}(S) \;\equiv\; \frac{\partial M_t}{\partial \ln p_{m,t}} \;=\; \frac{1}{A(M_t, S)}, \tag{E.4}$$

where $A(M_t, S)$ is given by (E.2). Differentiating with respect to S yields

$$\frac{\partial \varepsilon_{M,p}(S)}{\partial S} = -\frac{1}{A(M_t, S)^2} \frac{\partial A(M_t, S)}{\partial S}. \tag{E.5}$$

Since $A(M_t, S) > 0$ and $\partial A / \partial S \geq 0$ from (E.3), it follows that

$$\frac{\partial \varepsilon_{M,p}(S)}{\partial S} \;\leq\; 0, \quad \text{strict if } S > 0.$$

completing the proof that when wholesale price increases, the input-price semi-elasticity shrinks toward zero as bottlenecks tighten.

E.6.2 Capital–Price Response

The wholesale firm's intertemporal first-order condition is

$$E_t\Big[\Lambda_{t,t+1}\Big(\alpha\, p_{m,t+1}\, \Phi(M_{t+1}, S)^{1-\alpha}\, K_{t+1}^{\alpha-1} + (1-\delta)\Big)\Big] = 1.$$

Define

$$F\big(K_{t+1}, p_{m,t+1}, S\big) = 1 - E_t\Big[\Lambda_{t,t+1}\Big(\alpha\, p_{m,t+1}\, \Phi^{1-\alpha} K_{t+1}^{\alpha-1} + (1-\delta)\Big)\Big] = 0.$$

$$F_p \;\equiv\; \frac{\partial F}{\partial \ln p_{m,t+1}} \;=\; p_{m,t+1}\, \frac{\partial F}{\partial p_{m,t+1}}, \qquad F_K \;\equiv\; \frac{\partial F}{\partial K_{t+1}}.$$

Applying the implicit-function theorem to $F\big(K_{t+1}, \ln p_{m,t+1}, S\big) = 0$ yields

$$\varepsilon_{K,p}(S) \;\equiv\; \frac{\partial \ln K_{t+1}}{\partial \ln p_{m,t+1}} \;=\; -\frac{F_p}{F_K\, K_{t+1}}. \tag{E.6}$$

Signs of the two derivatives

$$F_K = -E_t\Big[\Lambda_{t,t+1}\,\alpha(\alpha-1)\,p_{m,t+1}\,\Phi^{1-\alpha}K_{t+1}^{\alpha-2}\Big] \;>\; 0 \quad (\alpha \in (0,1)),$$
$$F_p = -E_t\Big[\Lambda_{t,t+1}\,\alpha\,p_{m,t+1}\,\Phi^{1-\alpha}K_{t+1}^{\alpha-1}\Big] \;<\; 0.$$

Hence $\varepsilon_{K,p}(S) > 0$; a higher wholesale price raises desired future capital.

$$\varepsilon_{K,p}(S) = -\frac{F_p}{F_K\,K_{t+1}} = \frac{E_t\Big[\Lambda_{t,t+1}\,\alpha\,p_{m,t+1}\,\Phi^{1-\alpha}K_{t+1}^{\alpha-1}\Big]}{E_t\Big[\Lambda_{t,t+1}\,\alpha(1-\alpha)\,p_{m,t+1}\,\Phi^{1-\alpha}K_{t+1}^{\alpha-2}\Big]\,K_{t+1}}$$

$$\varepsilon_{K,p}(S) = \frac{1}{1-\alpha} \tag{E.7}$$

Thus, in this specification the capital–price elasticity is independent of both the bottleneck index S.

E.7 Additional Results

Figure E.1 illustrates the responses of key aggregate variables following a -1 percent annualized monetary policy shock in the baseline economy, which does not account for supply chain pressures. The shock leads to an immediate increase in output by 0.42%, while capital increases peaks at 0.05%. Inflation rises by 0.59%, investment increases by 1.29%, and consumption shows a peak increase of 0.03%. Additionally, inputs rise by 0.75%.

These magnitudes are generally consistent with the peak effects of monetary policy shocks estimated in previous literature. For instance, Christiano et al. (2005) found that investment increases by approximately 1%, consumption by 0.2%, and output by 0.5%. Similarly, Sims and Wu (2021) estimated that after a conventional monetary policy shock,output rises by approximately 0.5%, inflation increases by about 0.15% and investment responds with a 2% increase, while inflation rises by around 0.6% on impact. Furthermore, Sims et al. (2023)3), using the standard three-equation New Keynesian model, found that output increases by approximately 0.6%, with inflation rising by 0.8%.

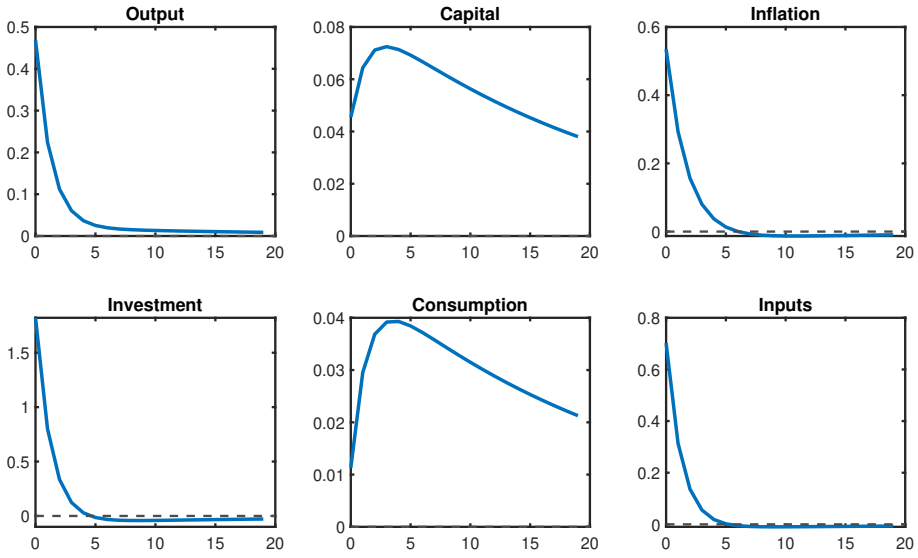


Figure E.1: Exogenous Monetary Policy in the Baseline Model

Notes: This figure plots the impulse response function to an unanticipated 100-basis-point cut to the annualized policy rate. when the economy does not face supply chain pressures. The responses of output, capital, investment, consumption, and inputs are expressed in percentage points, while the response of inflation is expressed in annualized percentage points.