The Macroeconomic Effects of Global Supply Chain Shocks

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Abstract

This paper provides evidence that global supply chain shocks are key drivers of business cycle fluctuations, introducing a novel identification strategy based on a narrative analysis of price surcharges from the three largest container shipping companies. Negative shocks cause a persistent rise in consumer prices and a prolonged decline in economic activity. Sectoral impacts vary with exposure to global supply chains, measured by the share of inputs sourced from abroad. Spillovers extend to non-tradable sectors. These shocks accounted for up to 51% of the post-pandemic inflation. If there had been only global supply chain shocks with no monetary or fiscal stimulus, recovery would have taken 18 months longer. Global supply chain shocks explain 35% of the long-run variance of consumer prices and 24% of industrial production over the business cycle.

Keywords: Business Cycles, Global Supply Chain Shocks, Supply Chain Disruptions, Narrative Identification, Post-Pandemic Inflation

JEL Codes: E31, E32, F14, R41

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1 Introduction

The surge in post-pandemic inflation in the United States has sparked an intense debate over its primary causes. Several studies attribute the majority of the price surge to demand-side forces, such as pent-up consumption and expansionary fiscal policy, while others point to supply-side factors, including energy price shocks and production bottlenecks. Despite disagreeing on the relative importance of demand versus supply forces, both academics and policymakers uniformly acknowledge global supply chain disruptions as key contributors to the post-pandemic inflation.

However, we still lack a credible exogenous measure of global supply chain shocks and a robust estimate of their macroeconomic consequences. This limitation reflects an identification challenge arising from the inherently global and heterogeneous nature of these shocks. Global supply chain disruptions can be caused by port equipment failures, labor strikes, extreme weather events, and piracy, which also makes them difficult to measure consistently. In practice, researchers rely on indicators such as delivery times, port congestion, and shipping costs, but these are themselves endogenous to fluctuations in global demand and production activity. Consequently, the extent to which shocks to the global supply chain drive business cycle fluctuations remains an open question.

Macroeconomic theory provides clear reasons why shocks to the global supply chain might have large aggregate effects. Acemoglu et al. (2012) show that when a central supplier provides inputs to a disproportionately large number of downstream industries, idiosyncratic shocks to that sector can generate significant aggregate fluctuations. The global supply chain plays precisely this role: between 80% and 90% of internationally traded goods travel by sea, and roughly two-thirds—worth over $8 trillion—move in containers (Notteboom, Pallis and Rodrigue, 2022). Moreover, a handful of global carriers dominate the market and have fused the world's major trade lanes—East–West, Trans-Pacific, and Trans-Atlantic—into a single, tightly coupled global supply chain by linking vessels through key global ports. In line with the granularity argument of Gabaix (2011), idiosyncratic shocks to these dominant players or key ports can generate aggregate fluctuations. Recent research from Barrot and Sauvagnat (2016), Acemoglu and Tahbaz-Salehi (2020, 2025), Elliott, Golub and Leduc (2022) and Elliott and Golub (2022) shows that complex production networks in equilibrium are inherently fragile to small shocks that simultaneously disrupt multiple supply relations. Because the global supply chain physically intermediates all the other supply chains, localized shocks can cascade through it, disrupting supply relations across the entire global economy.

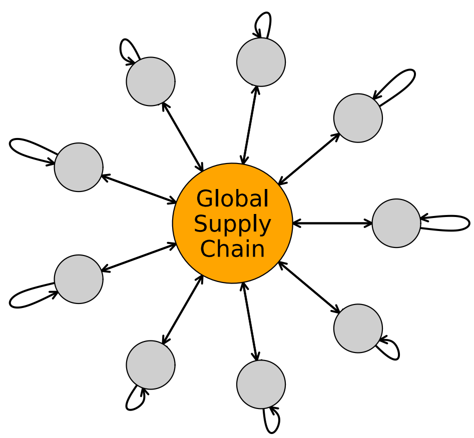

Figure 1: The global supply chain as the central hub of the global economy

Notes: The figure provides a stylized representation of the global economy as a star network. Each peripheral node represents an economy that maintains both domestic (self-loops) and international supply relations. All international supply chains are mediated by the global supply chain, which functions as the central hub of the network.

This paper makes five contributions. (i) I propose a new strategy to identify exogenous shocks to the global supply chain. (ii) I show that small shocks to the global supply chain generate significant aggregate fluctuations in the US economy. (iii) I find that these shocks produce stagflationary effects across all tradable sectors and spill over to non-tradable services in line with Guerrieri et al. (2022)'s characterization of the transmission mechanism of Keynesian supply shocks. (iv) I contribute to the debade about the causes to the post-pandemic inflation, concluding that these shocks were the primary contributors to inflation in 2021 and exerted substantial downward pressure on the economic recovery. (v) Lastly, I show that shocks to the global supply chain account for a significant share of the variability in macroeconomic activity over the business cycle.

This paper is not the first one to study the macroeconomic effects of shocks to the global supply chain. A growing empirical literature has approached the question in two main ways. The first combines measures of global supply chain bottlenecks, such as the Global Supply Chain Pressure Index (GSCPI) of Benigno et al. (2022) or the Average Congestion Rate index of Bai et al. (2024), with structural vector autoregressive (SVAR) models identified through sign or narrative-sign restrictions (Finck and Tillmann, 2022; Gordon and Clark, 2023; De Santis, 2024; Ascari, Bonam and Smadu, 2024; Bai et al., 2024), or similar time-series techniques (Carrière-Swallow et al., 2023). The second exploits cross-sectional variations around exogenous events such as the Tōhoku earthquake (Boehm, Flaaen and Pandalai-Nayar, 2019; Carvalho et al., 2021). Both approaches face important limitations. In the first, key variables such as commodity prices, delivery times, shipping costs, and port congestion are endogenously influenced by global economic activity (Baumeister and Hamilton, 2019; Alquist, Bhattarai and Coibion, 2020; Delle Chiaie, Ferrara and Giannone, 2022; Baumeister, Korobilis and Lee, 2022). This complicates causal inference, as these indicators conflate the effects of supply chain disruptions with those of other macroeconomic shocks. In the cross-sectional literature, the main concern is external validity: identifying a consistent set of truly exogenous disruptions is inherently challenging, given their diverse and global nature, which encompasses extreme weather events, labor strikes, port closures, geopolitical conflicts, and piracy.

I overcome these issues by developing a new strategy to identify global supply chain shocks based on narrative analysis of price surcharge announcements from the three largest containerized shipping companies, which collectively hold nearly 50% of the market share and up to 70% through strategic alliances. I collect approximately 7,000 daily price and surcharge updates published on their websites from 2014 to 2024, focusing exclusively on five key regions: Europe, the Middle East and Sub-Indian Continent, East Asia, Oceania, and

North America. These updates range from general freight increases to other extraordinary surcharges influenced by supply and demand dynamics, expectations, and strategic behavior. While the announcements often reflect both supply and demand factors, when surcharges arise from extraordinary, unpredictable events, the companies frequently cite explicit reasons. Using a keyword-based algorithm adapted from Baker, Bloom and Davis (2016), I first isolate a subset of 369 surcharge announcements that contain terms objectively associated with exogenous supply-side events, such as strikes, natural disasters, armed conflicts, piracy and operational disruptions. I then conduct a narrative analysis of these announcements, cross-validating them with external sources, in an adaptation of the narrative identification strategy widely employed in the study of oil shocks (Hamilton, 1985, 2003; Caldara, Cavallo and Iacoviello, 2019; Qureshi and Ahmad, 2025), monetary policy shocks (Romer and Romer, 2004; Aruoba and Drechsel, 2024), and fiscal shocks (Ramey and Shapiro, 1998; Romer and Romer, 2010; Ramey, 2011). This process allows me to identify 62 exogenous supply chain disruptions, measured as price surcharges in US dollars per Forty-foot Equivalent Unit (FEU) dry container.

Using the FEU price surcharges as an external instrument within a Proxy-SVAR framework, I estimate the dynamic causal effects of shocks to the global supply chain on the US economy at both the aggregate and sectoral levels. I find that negative shocks produce aggregate stagflationary effects, with a persistent rise in consumer prices and a prolonged economic slowdown marked by lower industrial production and higher unemployment. At the sectoral level, I find declines across all production sectors, with sustained increases in all consumer price categories. Sectoral output dynamics mirror aggregate responses: an initial decline, peaking within the first few quarters, and a gradual return to steady state over three years. However, the magnitude of these effects varies across sectors. A sector's exposure to the global supply chain, measured by the share of intermediate inputs imported from abroad (Baldwin, Freeman and Theodorakopoulos, 2023), explains this heterogeneity. I find that greater exposure is associated with more severe production declines. Moreover, sectors that experience the largest output reductions also exhibit the most significant and persistent pass-through to consumer prices.

I also document significant spillover effects into non-tradable service sectors. Although services are not directly exposed to the global supply chain, service activity and employment decline with a lag. These findings support the conclusions of Guerrieri et al. (2022) about the propagation of sectoral shocks in a multi-sectoral economy. In line with their characterization of Keynesian supply shocks, global supply chain disruptions create slack in the tradable sector, with output falling below potential, causing income loss that depresses spending in the non-tradable sector and generates involuntary unemployment.

I also contribute to the debate about the main causes of the post-pandemic inflation. My estimates indicate that shocks to the global supply chain were the primary driver of inflation in 2021, accounting for an average of 51% of the price increase. While my analysis does not rule out the significant role of demand,[1] it shows that these shocks were the primary contributors in the early stage of the price surge in 2021. While from 2022 onward other factors, such as demand forces, fiscal stimulus, and other supply shocks,[2] increasingly shaped inflation dynamics, global supply chain shocks remained a significant force, contributing, according to my estimates, 32%, 30%, and 22% to consumer price increases in 2022, 2023, and 2024, respectively. Regarding economic recovery, these shocks exerted sustained downward pressure. In a counterfactual scenario with only global supply chain shocks, industrial production would have required an additional 18 months to return to pre-pandemic levels, from November 2021 to May 2023.

I show more broadly that shocks to the global supply chain are key drivers of business

[1] Di Giovanni et al. (2022), Giannone and Primiceri (2024), Garcia Revelo, Levieuge and Sahuc (Forthcoming), and Bergholt et al. (Forthcoming) attribute the majority of the price surge to strong pent-up demand, while Cochrane (2022), Di Giovanni et al. (2023*a*,*b*), Jordà and Nechio (2023), Faria-e Castro (2024), and Hazell and Hobler (2024) emphasize the inflationary impact of fiscal stimulus.

[2] On the supply side, Bernanke and Blanchard (2023, 2024) identify shocks to energy and food prices, alongside widespread supply disruptions in key sectors, as key inflationary drivers. Caldara, Iacoviello and Yu (2025) argue that supply forces primarily drove inflation, Comin, Johnson and Jones (2023) find that potentially-binding capacity constraints explain half of the rise in inflation, while Goda and Soltas (2022), Hobijn and Sahin (2022), Lee, Park and Shin (2023) discuss the role of potential shocks to productive capacity.

cycle fluctuations.[3] They explain more than one-third of consumer price variability, a quarter of industrial production variability, and about 10% of unemployment variability over the business cycle.

The remainder of the paper is organized as follows: Section 2 discusses the identification design and the construction of the instrument. Section 3 outlines the econometric approach and examines the propagation of global supply chain shocks at aggregate and sectoral levels. Section 4 evaluates their cumulative impact on pandemic-era inflation and economic recovery. Section 5 assesses the quantitative role of global supply chain shocks as drivers of business cycle fluctuations. Section 6 performs some robustness checks, and Section 7 concludes.

2 Narrative Identification

The identification strategy builds on the narrative analysis of surcharge announcements from the world's three largest shipping companies. When confronted with exogenous disruptions that increase operational costs, shipping companies respond by imposing price surcharges on shippers. The idea is to construct a series of price surcharges correlated exclusively with exogenous supply-side disruptions that will serve as an external instrument in a SVAR framework to structurally identify the unobserved global supply chain shocks. Before detailing the procedure for identifying such disruptions, I first provide evidence on the containerized shipping market's oligopolistic structure and the role played by price surcharges in the measurement and transmission of shocks across the supply chain network.

[3] While finalizing this paper, I learned of Känzig and Raghavan (2025)'s measure of supply chain disruptions constructed from high-frequency movement of the Baltic Exchange Dry Index during exogenous events at the Panama and Suez Canals. Their instrument captures shocks to dry bulk commodities, while my measure reflects disruptions to high-value containerized goods spanning intermediate and final products. Their analysis also centers on specific maritime chokepoints, which naturally gives it a more localized geographic focus relative to my measure, which incorporates disruptions across major global trade corridors, including the Trans-Pacific, Trans-Atlantic, and key Asian hubs. Despite these differences, their preliminary results point to the same conclusion: global supply chain disruptions are an important source of business cycle fluctuations.

2.1 The Containerized Shipping Industry

From 2014 to 2024, the containerized shipping industry was dominated by three major alliances: the 2M Alliance, formed by Mediterranean Shipping Company (MSC) and A.P. Møller–Mærsk A/S (Maersk); the Ocean Alliance, comprising Compagnie Maritime d'Affrètement–Compagnie Générale Maritime (CMA CGM), COSCO, and Evergreen; and THE Alliance, including Hapag-Lloyd, Ocean Network Express (ONE), Yang Ming Marine Transport Corporation, and Hyundai Merchant Marine (HMM). These alliances collectively controlled approximately 80-90% of global container shipping capacity by the early 2020s, reflecting the concentrated structure of the industry and enabling carriers to coordinate vessel deployment, share terminal infrastructure, and reduce route duplication, thereby achieving significant economies of scale. High fixed costs, substantial barriers to entry, and the need for globally integrated service networks reinforced market power among a small group of dominant carriers. The three largest shipping companies, MSC, Maersk, and CMA CGM, together account for nearly 50% of the global container shipping market, with operations that span all major trade corridors, from Asia to Europe, North America, and beyond.

Crucially, the interconnectedness of major trade lanes, including the East-West, Trans-Pacific, and Trans-Atlantic corridors, effectively creates a de facto single global shipping route. Vessels routinely interconnect at major hubs such as Singapore, Shanghai, Rotterdam, and Los Angeles–Long Beach, transforming the global network into an integrated and interdependent system (Fan, Wilson and Dahl, 2012). As a result, disruptions in one region, such as the 2021 Suez Canal blockage or the 2022 Shanghai port backlog, quickly reverberated across the entire network, generating ripple effects on capacity, schedules, and freight pricing worldwide.

Within this tightly interconnected system, shipping companies respond to demand or supply shocks by imposing price surcharges on shippers. These surcharges serve as a key mechanism to recover rising operational costs and, at the same time, to rebalance container flows by disincentivizing shipments into already congested or container-saturated regions.

However, because surcharges are typically applied across entire trade lanes, a localized disruption, originating in, say, a single port or country, can lead to system-wide price increases, affecting routes far removed from the original shock. In this way, price surcharges function as transmission vehicles: they not only quantify the magnitude of the disruptions but also propagate the increasing operational costs across multiple trade lanes through the combined forces of oligopolistic power and network interdependence. MSC, MAERSK, and CMA CGM published more than 7,000 price and surcharge updates on their websites between February 2014 and December 2024, reflecting changes in container shipping costs across a wide range of global routes and ports. I will now describe the methodology used to isolate exogenous supply-side disruptions to the global supply chain from the narrative record of price surcharges.

2.2 Identifying Exogenous Disruptions

Methodology.— To construct a narrative-based measure of exogenous global supply chain disruptions, I begin by systematically collecting price surcharge announcements from the websites of the three largest container shipping companies. Specifically, I compile 1,218 surcharges from MSC (February 2014–December 2024), 2,450 from Maersk (March 2019–December 2024), and 3,222 from CMA CGM (March 2015–December 2024). These announcements include various surcharge types, often accompanied by textual justifications provided by the carriers themselves.

I focus exclusively on surcharges related to the three major trade routes, Trans-Pacific, East-West and Trans-Atlantic corridors, which form a unified global shipping network. I exclude routes serving South America and West Africa, as well as surcharges involving ports with annual throughput below 250,000 FEUs, which are less relevant for capturing globally systemic disruptions.

To isolate surcharges only related to exogenous supply-side disruptions, I adopt a keyword-based algorithm adapted from Baker, Bloom and Davis (2016). Using a pre-defined list of terms associated with operational failures, labor strikes, natural disasters, geopolitical conflicts, and partial or full blockages of maritime chokepoints with consequent re-routing (see online Appendix B), I isolate a subset of 369 surcharge announcements that contain one or more terms plausibly linked to unpredictable supply-side disruptions.

Following this automated screening, I conduct a narrative analysis of the explanation accompanying each of the 369 candidate surcharge announcements to verify that it reflects an exogenous supply-side disruption unrelated to broader macroeconomic or demand-driven forces. When the textual description is insufficiently detailed, I cross-validate the announcement using external sources such as local newspapers, industry blogs, and port authority statements.

Applying the criteria.— For illustration, I include below a price surcharge announcement published by Maersk on January 8, 2024, which suspended transit through the Red Sea due to multiple Houthi rebel attacks on commercial vessels, rerouted vessels via the Cape of Good Hope, and introduced a Transit Disruption Surcharge (TDS):

> ***08 January 2024 – Transit Disruption Surcharge***
>
> *As we have been communicating since mid-December/23, Maersk is continuing monitoring developments around the Red Sea / Gulf of Aden and making carefully considered changes to services to ensure the safety of our seafarers, vessels and customers' cargo.*
>
> *The situation is constantly evolving and remains highly volatile, and all available intelligence at hand confirms that the security risk continues to be at a significantly elevated level. We have therefore decided that all Maersk vessels due to transit the Red Sea / Gulf of Aden will be diverted south around the Cape of Good Hope for the foreseeable future.*
>
> *By suspending voyages through the Red Sea / Gulf of Aden, we hope to bring our*

customers more consistency and predictability despite the associated delays that come with the re-routing.

The previously announced surcharges for all cargo on vessels affected by the disruptions around the Red Sea / Gulf of Aden remain in effect:

Transit Disruption Surcharge effective as from actual sailing date 10/01/2024 until further notice.

To give you as much clarity and predictability as possible, TDS will apply only to bookings confirmed as from 21/12/2023 (global announcement date) and departure date as from 10/01/2024 onwards.

TDS - USD per container	**20DRY**	**40DRY**	**40HREF**
All shipments diverted from Suez	200	400	450

The narrative analysis of the surcharge establishes its exogenous supply-side cause. When the announcements lack explicit reasons for the surcharge, I complement the narrative analysis of the announcement with external sources to assess whether an exogenous supply-side disruption is plausibly the cause of the surcharge. For example, CMA CGM introduced a Port Congestion Surcharge (PCS) on March 27, 2023, for shipments departing from Mersin, Turkey:

27 March 2023 – PCS in Mersin, Turkey

We inform our customers that we are experiencing important delays in Mersin, Turkey between congestion/waiting time plus berth time on the current vessels berthing sequences with following impacts: (i) laden cargo lead-time is being increased; (ii) empty equipment re-loading / repositioning frequency is affected; (iii) operating costs are increased.

In this respect please be informed that CMA CGM will be implementing a Port Congestion Surcharge in Mersin as follows:

- ***From:*** *Mersin, Turkey*
- ***To:*** *Mediterranean & Adriatic, Black Sea, North Africa & Portugal, South America, Central America & Caribbean, Mexico West Coast, Windward, Guyana North Brazil, Middle East Gulf, Red Sea, North & South East Asia, China, Hong Kong SAR*
- ***Cargo:*** *Dry*
- ***Applicable from:*** *March 27th, 2023, loading date (April 25th, 2023 for Puerto Rico)*
- ***Amount:*** *USD 100 per TEU*

Although CMA CGM did not specify the reason for the PCS, I classify this surcharge as a response to an exogenous supply-side disruption. Several sources confirmed that the cause of the surcharge was a devastating 7.8-magnitude earthquake that struck southern Turkey in February 2023, causing extensive damage to port infrastructure and regional road networks.[4] Trucking activity around Mersin was largely disrupted, and the major nearby port of Iskenderun ceased operations due to fire damage caused by the earthquake. As a result, vessels were rerouted to Mersin, leading to increased delays and congestion.

Morphology of exogenous disruptions.— Overall, the narrative analysis leads to the identification of 62 exogenous disruptions. Among these, 14 events involve major maritime chokepoints, where disruptions affect all trade routes transiting through them. These include four weather-related disruptions at the Panama Canal, driven by prolonged drought and reduced water levels; four operational disruptions at the Suez Canal, caused by the 2021 grounding of the Ever Given and other blockage-related incidents; one conflict-related disruption in the Strait of Hormuz, linked to an Iranian attack on two oil tankers; and four

[4] See: Portcast (2023): *Impact of Türkiye–Syria Earthquake on the Shipping Industry*, Fox Business (2023): *Earthquake Sparks Massive Shipping Container Fire*, and Reuters (2023): *Iskenderun Port Operations Halted After Earthquake-Induced Fire.*

war-related events at the Bab el-Mandeb Strait, all stemming from Houthi rebel attacks and the broader civil conflict in Yemen. Beyond chokepoints, 8 additional events involve all ports along major trade corridors. These include disruptions on routes connecting Far East Asia (China, Taiwan, Hong Kong) to the United States and Europe, as well as five events along the Trans-Atlantic corridor, primarily caused by low water levels in the St. Lawrence Seaway. An additional 13 disruptions affect broader macro-regions, involving multiple ports or inland transport systems within the same country or trade area. These include, among others, a nationwide breakdown in India's inland transport system due to truck driver shortages; widespread disruptions across dry ports in the United States; strikes in southern France and nationwide in Spain; labor unrest in northern European ports (Le Havre and Dunkirk); operational challenges across all UK ports; and war-related disruptions to all Black Sea trade ports following Russia's invasion of Ukraine. Finally, 27 events are localized at individual ports, including high-traffic terminals such as Shanghai, Ningbo, Los Angeles–Long Beach, Felixstowe, Nhava Sheva, and Colombo, affected by either operational failures or strikes.

These disruptions are classified into four categories based on their underlying cause: operational, war and conflict, strikes, and extreme weather or natural disasters. Figure 2 illustrates the global distribution of identified supply chain disruptions, with each event categorized by its underlying cause. For disruptions affecting entire trade routes, only the busiest ports, measured by annual container throughput in FEUs, are shown to preserve visual clarity.

Operational disruptions, comprising nearly 53% of the total (33 events), include truck driver shortages, new port regulations increasing vessel and container processing times, infrastructure failures (e.g., crane breakdowns or bridge collapses), and full or partial blockages of strategic chokepoints. War and conflict-related disruptions account for 18% of events and involve port closures due to hostilities, particularly in the Middle East, and suspensions of trade routes in war zones, such as the Black Sea. Strikes represent 11% (7 events), comprising labor actions that affected port operations either locally or nationally. Finally, natural

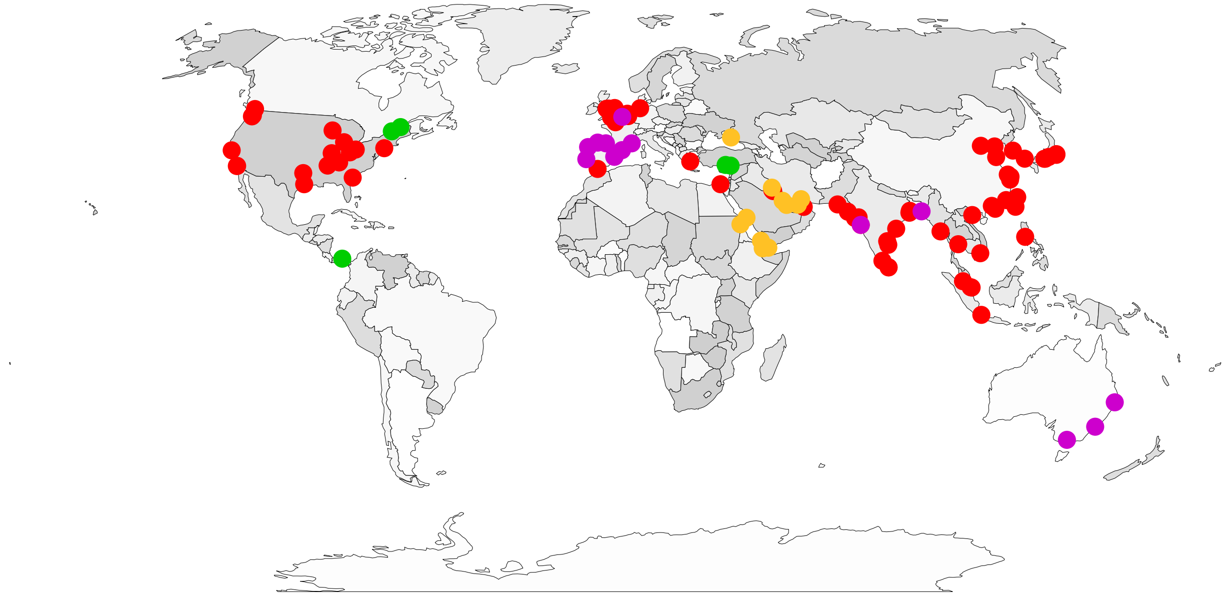

Figure 2: Locations of seaports and dry ports affected by exogenous disruptions.

Notes: The figure shows the geographic location of the identified exogenous supply chain disruptions, color-coded by underlying cause: operational, war/conflict, strike, and weather/natural disaster. For events affecting an entire trade route, only the largest ports in terms of annual dry FEU container throughput are shown to avoid overcrowding the visual.

disasters and extreme weather events, including exceptionally low water levels in the St. Lawrence seaway, the El Niño phenomenon impacting the Panama Canal, and the devastating earthquake in Turkey, constitute the remaining 18% of the total disruptions. An overview of all surcharge dates and data sources can be found in the online Appendix B.

2.3 Construction of the Instrument

Size and timing.— Building on the previously identified exogenous disruptions and their associated price surcharges, I now proceed with the construction of the narrative-based time series. For each disruption event, I first compute the average surcharge across affected trade lanes and shipping companies. These event-level averages are then aggregated within the month in which the surcharges were implemented, producing a cumulative monthly surcharge series measured in US dollars per FEU container.

In most cases, surcharges are applied either immediately or within the same month as the corresponding announcement. When implementation occurs in the following month, I assign the surcharge to the month of the implementation. This choice is motivated by several factors. Unlike central banks or institutions such as OPEC, shipping companies communicate pricing decisions less clearly and with limited coordination. Moreover, there is no evidence that market participants actively monitor or react to these announcements in real time. Even if such monitoring were to occur, substituting containerized ocean freight with alternative modes of transport, such as air freight, is both costly and logistically challenging. In addition, the contractual terms of container shipping are typically fixed well in advance, often for periods exceeding one year, further limiting the scope for anticipatory adjustments. These features of the industry imply that the demand for containerized shipping is relatively inelastic in the short run and that news effects are minimal. In the few cases where different carriers issue surcharges related to a single event across two consecutive months, I assign the event to the later month if most implementations occur after the midpoint of the earlier month.

The price surcharge series.— Figure 3 displays the resulting time series of price surcharges, expressed in US dollars per FEU dry container. This series represents a partial but timely measure of cumulative, exogenous supply-side disruptions in the global shipping network. Constructed at a monthly frequency over eleven years, it contains 46 non-zero observations corresponding to 62 individually identified disruption events. Of these, 19 events (approximately 40 percent) occurred before January 2020. It is worth noting that price surcharge data from Maersk are only available from January 2019 onward.

Among the identified exogenous price surcharges, only three negative values appear, each reflecting unexpected improvements in shipping conditions. These include the removal of the port congestion surcharge in Yemen in April 2018, following a UN-led conference that secured $2 billion in aid and introduced an economic plan to enhance humanitarian access and logistics; infrastructure upgrades at Shuwaikh Port in Kuwait in June 2019, where rapid progress on a berth development project reduced congestion and delays; and improvements in inland transportation and dry port operations in India in February 2023, where recent legislative reforms in customs and logistics policy spurred investment in freight infrastructure and centralized warehousing, including the completion of over 1,700 kilometers of high-capacity Dedicated Freight Corridors.

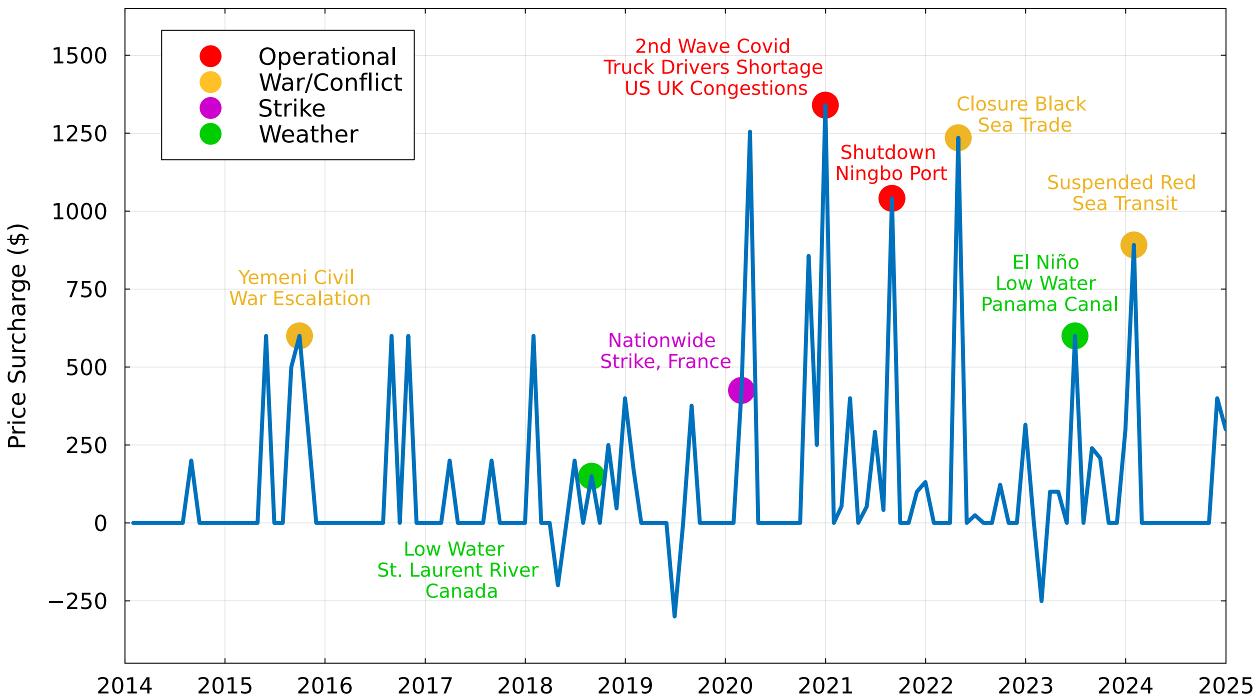

Figure 3: The Dry FEU Price Surcharge Series.

Notes: The figure shows the monthly dry FEU surcharge series, expressed in USD per container, constructed from the 62 identified exogenous disruptions. A selected subset of high-profile disruption events is also annotated and color-coded by underlying cause.

The largest positive surcharge, 1,340 dollars, was recorded in December 2020, driven by multiple concurrent shocks: a second wave of COVID-19 severely reduced port and trucking labor availability in the United States and the United Kingdom; newly introduced sanitation protocols for container handling in both countries lengthened operational times; and the escalation of the Yemeni conflict caused additional disruptions in the Bab el-Mandeb Strait.

Overall, the FEU price surcharge series closely aligns with major narrative episodes of disruption. Figure 3 highlights several major events in the container shipping network. These annotated episodes span each of the four disruption categories defined earlier: geopolitical conflict (e.g., the Yemeni civil war and Black Sea trade restrictions), operational failures (the August 2021 shutdown of Ningbo's Meishan terminal due to a COVID-19 outbreak), extreme weather events (e.g., El Niño-related congestion in the Panama Canal and low water levels in the St. Lawrence River), and labor strikes (e.g., the nationwide strike in France affecting all forms of transport). While these events represent only a subset of the 62 disruptions identified through the narrative analysis, they demonstrate that the FEU price surcharge series aligns closely with widely recognized, unpredictable supply chain disruptions.

Diagnostics— I perform a series of diagnostic checks on the FEU price surcharge series, examining autocorrelation, Granger causality in relation to a series of macroeconomic variables, and correlation with other structural shocks, following the approach outlined in Ramey (2016). I find no evidence of serial correlation: the p-value for the Ljung–Box Q-statistic testing whether all autocorrelations up to lag 20 are jointly zero is 0.39. I also find no evidence that the FEU price surcharge series is forecastable using a set of macroeconomic variables and other indicators that capture global uncertainty, trade, and geopolitical risk. The p-values from the Granger causality tests are well above conventional significance thresholds. Finally, I verify that the series is uncorrelated with other structural shock measures commonly used in the literature, including oil demand shocks, global economic activity shocks, and monetary policy shocks. All the results are available in the online Appendix A.

In Section 6, I further demonstrate that the results are not driven by any specific individual or subset of events. In particular, the main findings remain unchanged when excluding each disruption category individually, operational disruptions, wars and conflicts, labor strikes, and extreme weather events, as well as when excluding all COVID-related events.

3 Global Supply Chain Shocks & Business Cycle

The FEU price surcharge series can be seen as a partial measure of the unobserved global supply chain shock. Provided that this narrative-based series is correlated with the global supply chain shock and uncorrelated with other structural shocks affecting the economy, I use it as an external instrument within a Vector Autoregression (VAR) framework. This approach, also known as a Proxy-SVAR or SVAR-IV, focuses exclusively on identifying the structural shock of interest and builds on the extensive literature on the identification of structural VARs using external sources of exogenous variation, as developed by Stock (2008), Mertens and Ravn (2013), Stock and Watson (2018), and Montiel Olea, Stock and Watson (2021).

3.1 Econometric Framework

Consider the stationary reduced-form VAR(p) model:

$$\boldsymbol{y}_t = \boldsymbol{\Pi}\boldsymbol{x}_{t-1} + \boldsymbol{\epsilon}_t. \tag{1}$$

The k x 1 vector $\boldsymbol{x}_{t-1} = (\boldsymbol{1}, \boldsymbol{y}'_{t-1}, \ldots, \boldsymbol{y}'_{t-p})'$ contains an intercept and p lags of each of the variables ($k = 1 + pn$) and $\boldsymbol{\epsilon}_t$ is an n x 1 vector of reduced form innovations such that $\boldsymbol{\epsilon}_t \sim (\boldsymbol{0}, \boldsymbol{\Omega})$. The n x k matrix of reduced-form coefficients $\boldsymbol{\Pi}$ is estimated by OLS. I now assume that the model is invertible, i.e. the reduced-form innovations are a linear combination of the structural shocks:

$$\boldsymbol{\epsilon}_t = \boldsymbol{A}^{\boldsymbol{-1}}\boldsymbol{u}_t. \tag{2}$$

where $\boldsymbol{A}^{\boldsymbol{-1}}$ is the n x n structural impact matrix and $\boldsymbol{u}_t$ is the n x 1 vector of mutually uncorrelated structural shocks, i.e. $\boldsymbol{u}_t \sim (\boldsymbol{0}, \boldsymbol{D})$, where $\boldsymbol{D} = diag(d_{11} \ldots d_{nn})$. In Section 6, I formally test the invertibility assumption using the procedures outlined in Plagborg-Møller and Wolf (2022) and Hamilton (Forthcoming), and fail to reject the null hypothesis of invertibility for the baseline empirical model. The invertibility assumption implies

$$\boldsymbol{\Omega} = \boldsymbol{A}^{-1}\boldsymbol{D}(\boldsymbol{A}^{-1})'. \tag{3}$$

Since the VAR is stationary, (1) yields a VMA(∞) representation of the form

$$\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{\Psi}_h \boldsymbol{\epsilon}_{t-h}. \tag{4}$$

where the weights $\boldsymbol{\Psi}_h$ are functions of the reduced-form coefficient matrix $\boldsymbol{\Pi}$. Given the invertibility assumption, I obtain the structural vector moving average representation

$$\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{\Psi}_h \boldsymbol{A}^{-1} \boldsymbol{A}\, \boldsymbol{\varepsilon}_{t-h} = \sum_{h=0}^{\infty} \boldsymbol{\Theta}_h \boldsymbol{u}_{t-h}. \tag{5}$$

where $\boldsymbol{\Theta}_h = \boldsymbol{\Psi}_h \boldsymbol{A}^{-1}$ is the n x n matrix of structural responses to the vector of structural shocks that happened h periods before. Without loss of generality, I order the global supply chain shock as the first element (u_{1t}) of the vector of structural shocks $\boldsymbol{u}_t$; therefore, I aim to identify the first column of $\boldsymbol{A}^{-1}$, denoted by the vector $\boldsymbol{h}_1$.

Inference via External Instrument.— The identification strategy consists of using the stationary series of FEU price surcharges (Z_t) as external instrument. The instrument must be relevant

$$E[Z_t u_{1t}] = \alpha \neq 0 \tag{6}$$

and it must be exogenous to the other structural shocks

$$E[Z_t \boldsymbol{u}_{2:nt}] = \boldsymbol{0}. \tag{7}$$

Here $\boldsymbol{u}_{2:nt} = (u_{2t} \ldots u_{nt})'$ is the $(n-1)$ x 1 vector of all the other structural shocks. Under the two conditions above and the invertibility assumption, the structural impact vector $\boldsymbol{h}_1$ is identified up to a constant of proportionality (Stock and Watson, 2016; Baumeister and Hamilton, 2024). I resolve the scale ambiguity by defining an increase in the structural shock u_{1t} as an event that raises the observed variable y_{1t} by δ units

$$\widetilde{\boldsymbol{h}}_1 = (E[Z_t \boldsymbol{\epsilon}_{2:nt}]/E[Z_t \epsilon_{1t}]) \ \times \ \delta \tag{8}$$

subject to $\boldsymbol{\Omega} = \boldsymbol{A}^{-1}\boldsymbol{D}(\boldsymbol{A}^{-1})'$. Thus, if $\widetilde{\boldsymbol{h}}_1$ is identified and the VAR is invertible, the structural shock u_{1t}, its variance d_{11}, and the forecast error variance decomposition are identified.

Estimation with COVID.— The inclusion of 2020 data poses substantial challenges when estimating the model. Following Lenza and Primiceri (2022), I conceptualize COVID as a regime in which the innovation variance of the VAR is scaled up, while the autoregressive dynamics are unchanged. Formally, I define a regime indicator $s_t \in \{1, 2\}$, where $s_t = 1$ denotes normal times and $s_t = 2$ denotes the COVID period. The autoregressive coefficients of the VAR are held constant across regimes, $\boldsymbol{\Pi}_1 = \boldsymbol{\Pi}_2 = \boldsymbol{\Pi}$, but there is a marked scale-up in the innovation variance, $\boldsymbol{\Omega}_2 = \kappa^2\, \boldsymbol{\Omega}_1$, which generates large outliers. To implement this, I adopt a feasible Generalized Least Squares (GLS) iterative estimation procedure as suggested in Hamilton (Forthcoming), where the observations in the COVID sample are downweighted by the scaling factor κ, which is in turn estimated via Maximum Likelihood Estimation

$$\kappa^2 = \frac{1}{T_2 k} \sum_{t=1}^{T} (\boldsymbol{y}_t - \boldsymbol{\Pi}\boldsymbol{x}_{t-1})'\, \boldsymbol{\Omega}_1^{\mathbf{-1}}\, (\boldsymbol{y}_t - \boldsymbol{\Pi}\boldsymbol{x}_{t-1})\, \mathbb{1}\{s_t = 2\}. \tag{9}$$

Here T_2 is the total number of observations in the COVID regime, and k is the number of endogenous variables considered in the model. The same procedure is applied to the two-stage least squares estimation of the structural impact vector $\widetilde{\boldsymbol{h}}_1$. In the empirical analysis, I define the COVID regime as the period from January to December 2020.

3.2 Empirical Specification

The baseline specification of the empirical model employed in the analysis is a monthly VAR which comprises two global variables, the Global Supply Chain Pressure Index (GSCPI), ordered first as it serves as the instrumented variable, and the West Texas Intermediate (WTI) oil price, along with three US variables: Consumer Price Index (CPI), industrial production, and unemployment rate. The sample period begins in January 1998, with the start dates determined by the availability of the Global Supply Chain Pressure Index, which is available no earlier than January 1998. The end of the sample is set at December 2024. However, the first-stage estimation is conducted over the shorter period from January 2014 to December 2024, as price announcement data from the three major shipping companies are unavailable before January 2014.

The variables in the model are transformed into logarithms multiplied by 100, with two exceptions: the Global Supply Chain Pressure Index, which is retained in its original units as standard deviations from the mean, and the unemployment rate, which is expressed as a percentage. The VAR includes 12 lags.

3.3 Aggregate Fluctuations

I now provide evidence of the propagation mechanism of a negative shock to the global supply chain identified via external instrument. Figure 4 shows the structural Impulse Response Functions (IRFs) of the baseline model, normalized to a structural shock that increases the GSCPI by 0.5 units, corresponding to a \$1,340 price surcharge. This \$1,340 price surcharge corresponds to the peak surcharge observed by the instrument in December 2020. To contextualize this magnitude, a back-of-the-envelope calculation relates the \$1,340 surcharge to prevailing shipping costs. According to the Freightos Baltic Index, the average shipping cost for a FEU container in December 2020 was approximately \$2,650 across major global routes. Thus, the \$1,340 surcharge represents roughly 50% of the average shipping cost, providing a meaningful scale for evaluating the structural shock's magnitude. In all subsequent figures, the 68%, 80%, and 90% confidence bands are computed using 4,000 recursive wild bootstrap replications, in which the residuals are rescaled by independently drawn Rademacher random variables.

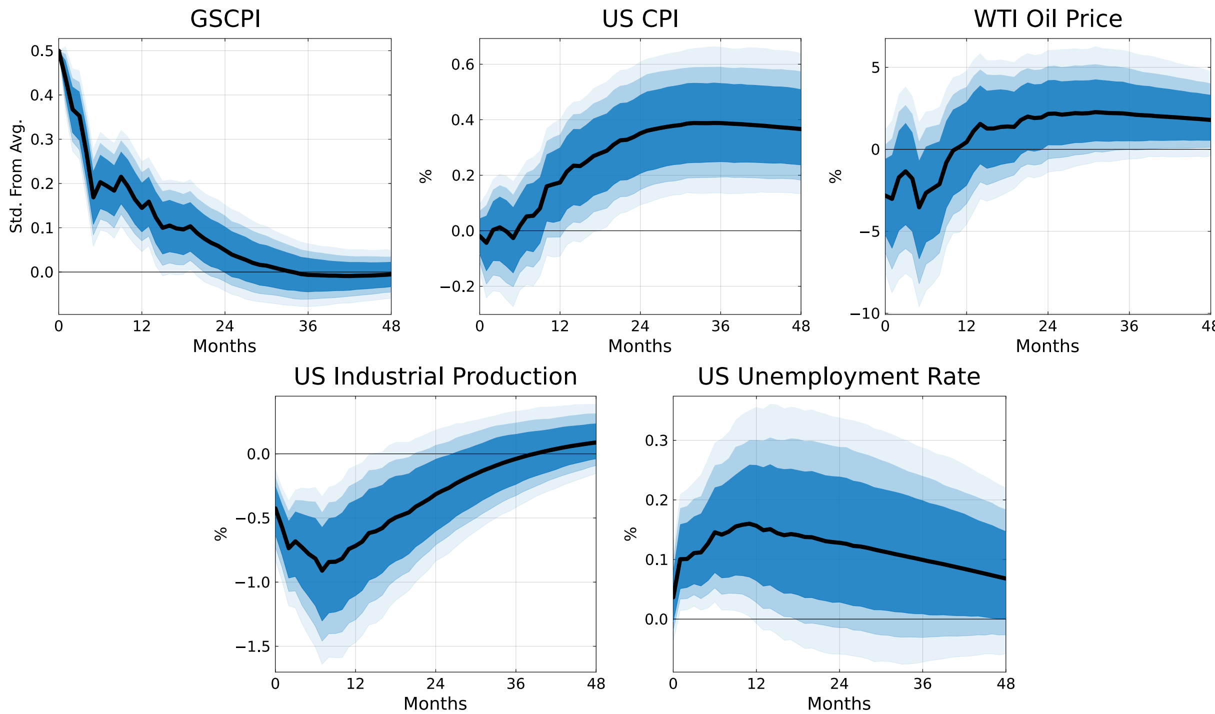

Figure 4: Structural Impulse Responses to a Global Supply Chain Shock.

Notes: Impulse responses to a global supply chain shock corresponding to a $1,340 price surcharge. The solid line is the point estimate and the shaded areas are 68, 80 and 90 percent confidence bands, respectively. First stage sample from January 2014 to December 2024. OLS regression: F-statistic: 18.18, R^2: 12.88%, Adjusted R^2: 12.17%. Feasible GLS regression to down-weight COVID period: F-statistic: 12.54, R^2: 9.25%, Adjusted R^2: 8.51%.

After the initial increase, the GSCPI reverses back and returns to its steady state after approximately three years. US consumer prices exhibit a sluggish and persistent increase, consistent with a price friction mechanism, and the response is highly statistically significant. In contrast, oil prices initially decline on impact and then gradually increase over time; however, the response is not statistically significant at conventional levels. Turning to real economic effects, the shock induces an immediate decline in industrial production, which reaches its lowest point after two quarters before gradually recovering. This response is highly statistically significant and persistent, with industrial production returning to its steady state no earlier than three years post-shock. The unemployment rate rises immediately, peaks after one year, and then gradually declines toward its steady state, remaining elevated for three additional years. At the peak, a supply-chain shock associated with a $1,340 price surcharge raises consumer prices by almost 0.4% and oil prices by 2.3%, while reducing industrial production by 0.9% and increasing unemployment by 0.16%.

Discussion.— At the aggregate level, a global supply chain shock functions as a cost-push shock in the New-Keynesian framework, raising firms' marginal costs due to higher transportation costs and shortages of intermediate inputs of production. As profit margins decline, firms reduce production and cut back on labor demand, leading to higher unemployment. Finally, the consumer price level rises gradually, reflecting both the pass-through of elevated input costs and delays in the delivery of final goods to markets. The most pronounced effect at impact is on production, which declines by 0.5% and takes nearly three years to return to its steady state. This persistence is consistent with the mechanisms emphasized by Alessandria et al. (2023), who show that temporary supply disruptions can generate protracted real effects. My findings also align with recent work quantifying the macroeconomic implications of supply chain disruptions. Bai et al. (2024) estimate relatively short-lived effects on real GDP and unemployment but persistent upward pressure on prices, patterns consistent with the price dynamics I obtain and with the evidence reported by Benigno et al. (2022) and Gordon and Clark (2023).

3.4 Wider Effects

To gain a deeper understanding of the macroeconomic propagation of shocks to the global supply chain, I examine their effects across key sectors of the US economy. I analyze sectoral responses in industrial production across major subsectors, the response of the aggregate service sector, and the response of consumer prices disaggregated by CPI category. I estimate impulse response functions by incorporating each variable individually into the baseline model, maintaining the same sample period as in the baseline specification.

Industrial production.— Figure 5 presents the IRFs for eight key industrial sectors alongside the aggregate industrial production series. I examine the two primary components of industrial production by industry group, manufacturing and mining, as well as the major subcategories within manufacturing: durable and nondurable goods. Additionally, I focus on food and beverage and motor vehicles and parts, two sectors critical for business cycle analysis and among the largest components of nondurable and durable goods, respectively. I also analyze materials and final products, the two main components of industrial production by market group. Final products are related to immediate pass-through to consumer prices, while materials, as intermediate inputs, capture persistent second-round effects on firms' marginal costs.

Following a negative shock to the global supply chain, all industrial production variables decline immediately, reach their trough within the first few quarters, and then recover to pre-shock levels between two and three years later. All impulse response functions are highly statistically significant, except for mining. This exception is unsurprising: despite US reliance on imported rare earth materials and other mining products, mining production has a localized supply chain, resulting in a response to global supply chain shocks that is not statistically different from zero. Manufacturing displays a sharper peak contraction than the aggregate index (1.32% vs. 0.9%). At their respective troughs, durable goods fall more than nondurables (1.44% vs. 0.77%), with total manufacturing lying in between. Motor vehicles and parts exhibit the largest peak decline (4.5%), while food and beverages show the smallest (0.45%), with a quick return to steady state. Among market groups, the peak response of materials (1.1%) exceeds that of final products (0.95%).

To interpret the heterogeneity in response magnitudes, I employ the look-through exposure metric developed by Baldwin, Freeman and Theodorakopoulos (2023). Constructed from the OECD's 2021 Inter-Country Input-Output (ICIO) tables, this metric measures the proportion of manufactured inputs sourced abroad by a US manufacturing sector relative

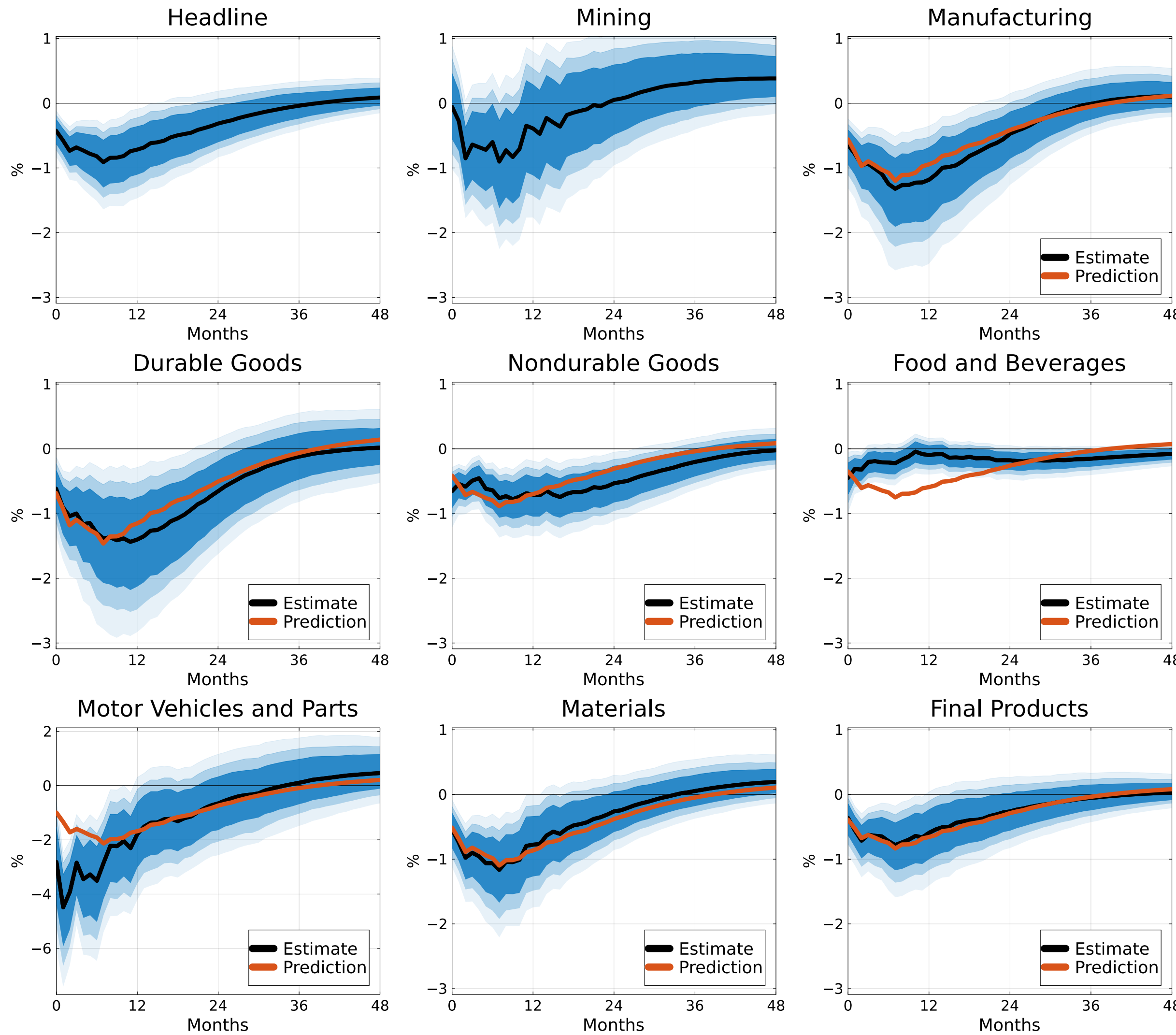

Figure 5: The Effects of Global Supply Chain Shock on US Industrial Productions.

Notes: Impulse responses to a global supply chain shock corresponding to a $1,340 price surcharge. The solid black line is the point estimate and the shaded areas are 68, 80 and 90 percent confidence bands, respectively. The orange line is the predicted sectoral IRF, derived by rescaling the headline industrial production IRF with the ratio of sectoral to headline look-through exposure measures. All subplots share the same y-axis scale, except for Motor Vehicles and Parts.

to total inputs of production, accounting for suppliers' own suppliers.[5] Using this metric, I construct predicted impulse responses by rescaling the headline IRF proportionally to each

[5]Baldwin, Freeman and Theodorakopoulos (2023) compute look-through exposure for 17 NAICS 31–33 manufacturing subsectors. I calculate exposure for broader manufacturing aggregates and the two market group series, using weights from the Industrial Production and Capacity Utilization (G.17) statistical release by the Board of Governors of the Federal Reserve System.

sector's relative exposure:

$$\widetilde{\mathrm{IRF}}_i = \widehat{\mathrm{IRF}}_h \times \frac{\mathrm{LT}_i}{\mathrm{LT}_h}. \tag{10}$$

Here, $\widehat{\mathrm{IRF}}_h$ is the impulse response function of the headline series, and LT_i and LT_h represent the look-through exposure for sector i and the headline, respectively.

These predicted responses, shown as orange lines in Figure 5, closely match the estimated sectoral IRFs, affirming that exposure to the global supply chain is a sufficient statistic to explain sectoral dynamics. Manufacturing, with a look-through exposure of 12.3%, is more exposed than the aggregate index, explaining its larger response. Durable goods are more exposed (15%) than nondurables (9.1%), and the total manufacturing response falls between the two, reflecting its weighted average composition. Motor vehicles and parts, with the highest exposure (21.9%), exhibit the most severe contraction, while food and beverages, with the lowest exposure (7.7%), experience the mildest. For food and beverages, the predicted IRF captures the response well on impact but overstates its persistence. This muted and short-lived response reflects the sector's limited reliance on foreign inputs and the prevalent use of capital goods that operate over multiple production cycles. Lastly, the different exposure of materials (11.3%) and final products (8.6%) explains the difference in their responses.

Services.— To assess the broader macroeconomic reach of global supply chain shocks, I examine their impact on the non-tradable sector, specifically services. Figure 6 presents the impulse responses of the ISM Services Activity Index, ISM Services Employment Index, and ISM Manufacturing Production Index to a negative shock corresponding to a \$1,340 price surcharge. Both services indicators exhibit no statistically significant response on impact, consistent with the fact that services are not directly exposed to global supply chain disruptions. However, approximately two quarters after the shock, both measures display a significant contraction, which gradually fades, returning to pre-shock levels within a year.

The inclusion of the ISM Manufacturing Production Index enables a meaningful structural comparison across tradable and non-tradable sectors, as all three indicators are survey-

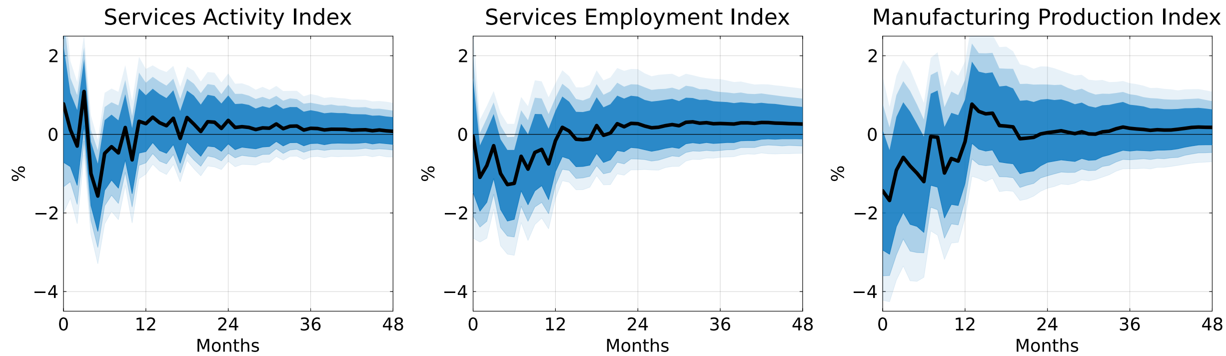

Figure 6: The Effects of Global Supply Chain Shock on Non-Tradable Sector.

Notes: Impulse responses to a global supply chain shock corresponding to a \$1,340 price surcharge. The solid black line is the point estimate and the shaded areas are 68, 80 and 90 percent confidence bands, respectively. All subplots share the same y-axis scale.

based and measured on comparable qualitative scales. The production index exhibits a sharp and immediate drop, capturing the direct effect of global supply chain shocks on the tradable goods sector. In contrast, the services activity index shows a delayed and smaller contraction, reflecting the presence of spillover effects rather than direct exposure. This dynamic, initial inertia followed by a transitory decline, suggests that the slack produced in the production sector by supply chain disruptions gradually propagates into the non-tradable sector. As workers in the production sector experience income losses, service firms face lower demand and adjust employment accordingly. Because these effects are indirect, the response of the services sector is both lagged and more muted relative to that of the production sector. Taken together, these results lend empirical support to the Keynesian supply shock propagation mechanism formalized by Guerrieri et al. (2022).

Consumer prices.— Figure 7 shows the responses of different components of CPI, including core, services, durable and nondurable goods, food and beverages, new vehicles, housing, and medical care, together with the headline response from the baseline model. A consistent pattern emerges across all components: each category exhibits a sluggish and persistent increase, with many remaining elevated even four years after the shock. This broad-based inflationary response reflects a gradual transmission from production disruptions to consumer prices, consistent with the presence of nominal rigidities.

The core CPI response is nearly identical to the headline CPI, reflecting the broad-based nature of the inflationary impact. This close alignment is consistent with the widespread decline observed across core production sectors.

The services CPI component exhibits a relatively mild yet persistent increase in response to a global supply chain shock. This inflationary pattern aligns with the observed declines in service sector activity and employment documented in Figure 6. Given that services are only indirectly exposed to global supply chain disruptions, the associated contraction in output is more limited. Accordingly, the pass-through to consumer prices is less pronounced, though still persistent.

Durable and nondurable goods exhibit markedly different inflationary responses, mirroring their respective production dynamics shown in Figure 5. Durables, which are more exposed to global supply chains, experience a stronger and more persistent price increase. This parallels the sharper and more prolonged contraction in durable manufacturing, particularly in sectors such as motor vehicles and parts. Nondurables, with lower exposure, exhibit a more modest price increase.

The divergence is even more pronounced when comparing food and beverages to new vehicles. The food and beverage category, which shows the smallest production response due to its localized supply chain structure, also displays the mildest CPI increase. By contrast, new vehicles, embedded in a highly globalized and input-intensive supply chain, exhibit the largest and most persistent CPI response, closely tracking the steep and extended production decline in motor vehicles and parts.

Lastly, I include housing and medical care to illustrate how sectors that appear largely insulated from international trade can still be affected by global supply chain disruptions. In addition, housing is the largest component of the CPI basket, making its inflationary dynamics particularly interesting. Both categories show persistent price increases following the shock, underscoring the economy-wide reach of supply chain disruptions, even in sectors not traditionally viewed as integrated in the global supply chain.

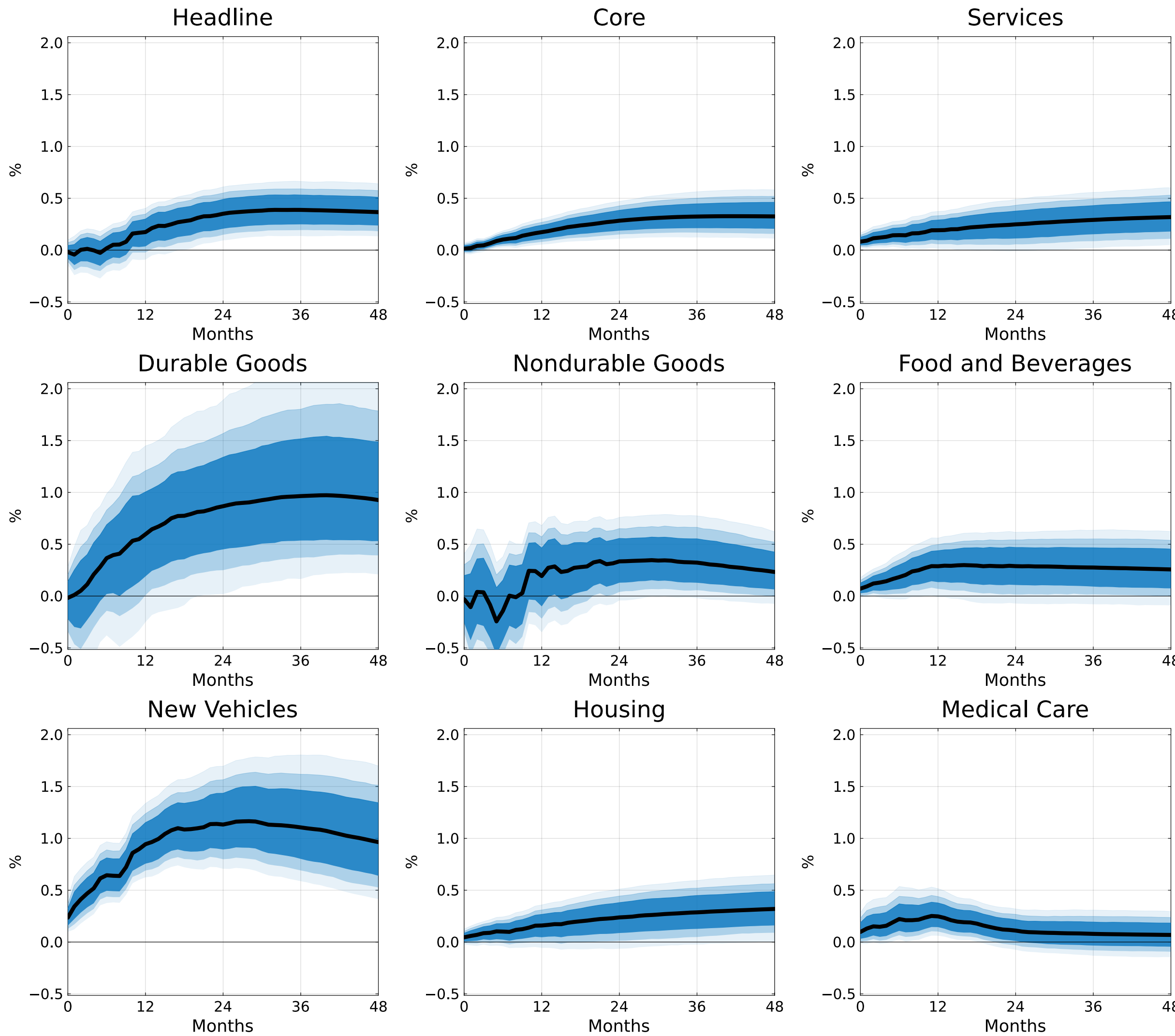

Figure 7: The Effects of Global Supply Chain Shock on US Consumer Prices.

Notes: Impulse responses to a global supply chain shock corresponding to a $1,340 price surcharge. The solid black line is the point estimate and the shaded areas are 68, 80 and 90 percent confidence bands, respectively. All subplots share the same y-axis scale.

Discussion.— Sectoral responses to a global supply chain shock exhibit similar qualitative dynamics but vary significantly in magnitude. Among production sectors, this heterogeneity is strongly correlated with each sector's degree of exposure to the global supply chain. Predicted impulse response functions, obtained by rescaling the IRF of aggregate industrial production by relative look-through exposures, closely match the estimated sectoral dynamics. This suggests that look-through exposure serves as a sufficient statistic for explaining cross-sectoral variation. Sectors experiencing the most pronounced output contractions, such as durable manufacturing, and in particular motor vehicles, also exhibit the strongest pass-through to consumer prices. While all CPI components respond persistently to the shock, durable goods and new vehicles stand out in both the size and persistence of their inflationary dynamics.

Beyond the tradable goods sectors, I find that global supply chain shocks spill over into non-tradable services. Although the responses of service activity and employment are more modest and transitory, they confirm the broader macroeconomic reach of these shocks. Services CPI also rises persistently, reflecting higher operational costs that are gradually passed on to consumers despite the sector's lower direct exposure to the global supply chain.

My sectoral analysis highlights why shocks to the global supply chain differ fundamentally from other cost-push shocks, such as oil supply shocks, undoubtedly the most studied in the literature. Oil shocks generate highly heterogeneous sectoral production responses, driven by factors like energy intensity in production, energy intensity of the goods produced, and demand substitutability (Davis and Haltiwanger, 2001; Hamilton, 2009; Herrera, Lagalo and Wada, 2011). Most industrial sectors show limited output responses to oil shocks, with price effects varying: some consumer price categories exhibit persistent increases, others are transitory, and some remain unaffected (Tenreyro, 2022; De Santis, 2024). In contrast to oil supply shocks, whose effects can be mitigated through the Strategic Petroleum Reserve or via the International Energy Agency cooperation, global supply chain disruptions lead to widespread output losses due to the physical unavailability of intermediate inputs sourced from abroad. While firms may receive monetary compensation for delays and can insure against fluctuations in shipping costs, they cannot insure against the missing deliveries of intermediate inputs, which disrupts production across all sectors.

4 Global Supply Chain Shocks and The COVID Era

The causes of the pandemic-era inflation have sparked intense debate in the literature, with competing explanations emphasizing either demand- or supply-side factors. While shocks to the global supply chain have been increasingly acknowledged as a contributing factor, all existing analyses rely on sign-restricted or narrative sign-restricted SVARs to assess their contribution to the pandemic-era inflation and economic recovery.

In this section, I contribute to the literature by providing a comprehensive analysis of the cumulative historical contribution of global supply chain shocks to the rise of consumer prices and the recovery of industrial production from January 2020 to December 2024, by leveraging the instrument and structural framework developed in Sections 2 and 3. In particular, I will answer two key questions: how significantly global supply chain shocks contributed to post-pandemic inflation and how these shocks influenced the recovery of economic activity.

4.1 Historical Decomposition

Given the econometric framework outlined in Section 3, if the structural impact vector $\widetilde{\boldsymbol{h}}_1$ is identified, Hamilton (Forthcoming) shows that the value of the first structural shock at date t, u_{1t}, can be recovered from the vector of the reduced-form innovations $\boldsymbol{\epsilon}_t$ as follows

$$u_{1t} = \left(\widetilde{\boldsymbol{h}}_1' \boldsymbol{\Omega}^{-1} / \, \widetilde{\boldsymbol{h}}_1' \boldsymbol{\Omega}^{-1} \widetilde{\boldsymbol{h}}_1 \right) \boldsymbol{\epsilon}_t \, . \tag{11}$$

Using the identified structural shock, I can estimate the contribution of the series of global supply chain shocks to the historical values of the variables included in the VAR model. The structural moving average representation from equation (5) implies:

$$\boldsymbol{y}_t(u_1) = \sum_{h=0}^{\infty} \boldsymbol{\Psi}_h \widetilde{\boldsymbol{h}}_1 u_{1t-h} \, . \tag{12}$$

Here, $\boldsymbol{y}_t(u_1)$ is referred to as historical decomposition, obtained as the infinite sum of the impulse responses to the global supply chain shock u_{1t-h} at each forecast horizon h, weighted by the corresponding structural impulse response coefficients $\boldsymbol{\Psi}_h \widetilde{\boldsymbol{h}}_1$.

4.2 Post-Pandemic Inflation

Figure 8 shows the cumulative historical contribution of global supply chain shocks to consumer prices from January 2020 to December 2024, measured in percentage deviations from the January 2020 level. The figure reveals that global supply chain shocks were key drivers of post-pandemic inflation, particularly during the first half of the sample period.

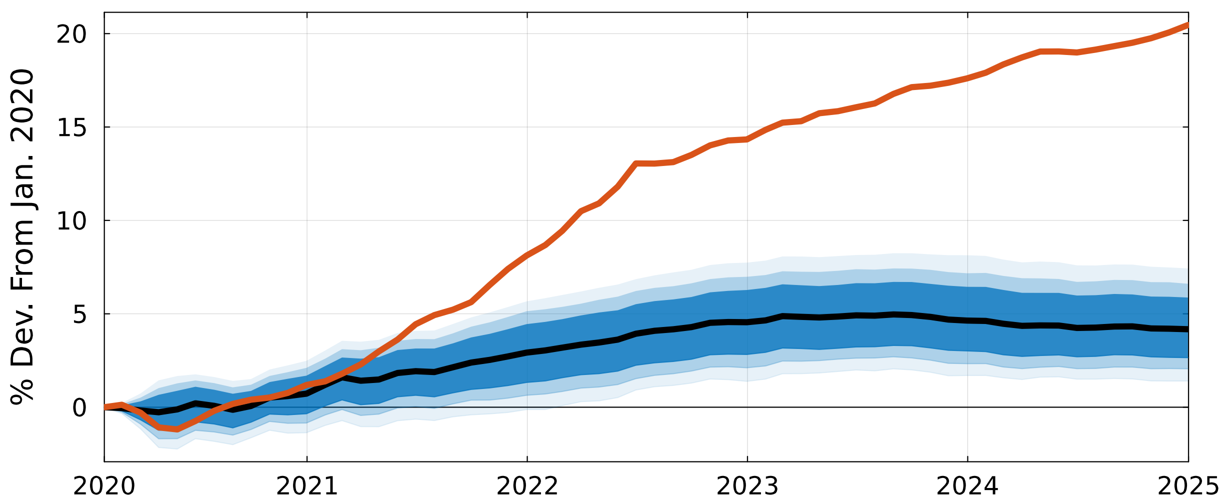

Figure 8: Historical Decomposition of Consumer Prices

Notes: The figure illustrates the historical contribution of global supply chain shocks to the US CPI, expressed as a percentage deviation from the pre-pandemic level (January 2020). The solid orange line is the actual series, the solid black line is the point estimates, and the shaded areas are 68, 80 and 90 percent confidence bands, respectively.

Beginning in the second half of 2020, severe disruptions at major hubs, such as the ports of Los Angeles and Long Beach (handling a combined 8.6 million FEUs annually), emerged alongside chokepoint disruptions in the Red Sea and Gulf of Aden due to the Houthi conflict. The delayed pass-through of these shocks triggered significant price increases in early 2021. The impact intensified through 2021 and 2022, exacerbated by global supply chain shocks associated with events such as the partial closure of China's Yantian port in Shenzhen (7 million FEUs annually, ranking 4th globally) from May to June 2021, and the shutdown of the Meishan terminal at Ningbo-Zhoushan port (16.3 million FEUs annually, 3rd globally) in August 2021, disrupting 25% of its container cargo capacity. The March 2021 Suez Canal obstruction, blocking a chokepoint responsible for 12% of global trade, further strained the system. In early 2022, stringent lockdown measures in Shenzhen and Shanghai, which impacted Yantian and Shanghai ports (the world's busiest, handling 21.8 million FEUs annually), and the Russian invasion of Ukraine, which disrupted Black Sea trade, led to the peak contribution to consumer prices observed in early 2023. Although the impact began to subside thereafter, new disruptions persisted into 2024, notably the January suspension of Red Sea transit, which forced rerouting via the Cape of Good Hope and prolonged inflationary pressures.

In 2021, global supply chain shocks accounted for an average of 51% of the surge in consumer prices, reflecting the scale of the unprecedented disruptions worldwide. My findings confirm the primary role of global supply chain shocks in shaping the early post-pandemic inflation dynamics documented by Bai et al. (2024). They are also consistent with the conclusions of Comin, Johnson and Jones (2023) and Caldara, Iacoviello and Yu (2025), who emphasize that shortage shocks and supply constraints, closely related to the disruptions captured by my proposed instrument, were key drivers of inflation during 2021. Similarly, Shapiro (2024) highlight the dominant contribution of supply-side factors in the early phase of the inflation surge, while Rubbo (2024) stresses the importance of aggregate supply shocks. My findings are also in line with Hobijn and Sahin (2022), whose decomposition of labor market aggregates suggests that the pandemic-induced labor supply shock contributed less to the early stage of post-pandemic inflation.

On the other hand, Di Giovanni et al. (2022) attribute the majority of the price surge in 2020-2021 to demand-side forces, a conclusion reaffirmed in their subsequent work (Di Giovanni et al., 2023a,b). The discrepancy most likely reflects differences in methodology: their model-based quantitative exercise, building on Baqaee and Farhi (2022), relies on feeding the model with demand and supply shocks constructed from calibration exercises or linear detrending methods.

Thus, while global supply chain shocks accounted for the majority of the 2021 inflation surge, the remaining variation could be largely attributable to demand factors and the substantial fiscal deficit, which makes my results consistent with the interpretation of Jordà and Nechio (2023), Garcia Revelo, Levieuge and Sahuc (Forthcoming), Faria-e Castro (2024), Giannone and Primiceri (2024), Hazell and Hobler (2024), and Bergholt et al. (Forthcoming). In the subsequent years, the contribution of global supply chain shocks to inflation moderated while remaining significant, at 32% in 2022, 30% in 2023 and 22% in 2024. This also aligns with findings from Goda and Soltas (2022), and Lee, Park and Shin (2023), who demonstrate that adverse shocks to productive capacity sustained elevated inflation levels from 2022.

4.3 Recovery of Industrial Production

Figure 9 shows the cumulative historical contribution of global supply chain shocks to industrial production for the period January 2020 - December 2024, measured in percentage deviations from production level observed in January 2020. The figure highlights the substantial downward pressure these shocks exerted on the economic recovery. By November 2021, industrial production had returned to its pre-COVID level, but in a counterfactual scenario with only global supply chain shocks, recovery would have been delayed until at least May 2023.

From January 2020, following reports of the COVID-19 outbreak in China, major shipping companies implemented extraordinary blank sailing omissions on key trade routes, notably on the Trans-Pacific and East-West corridors. By February 2020, severe disruptions in Chinese ports, as reported by MSC, led to critical shortages of refrigerated container plugs and prevented vessels from discharging at designated ports. These disruptions were

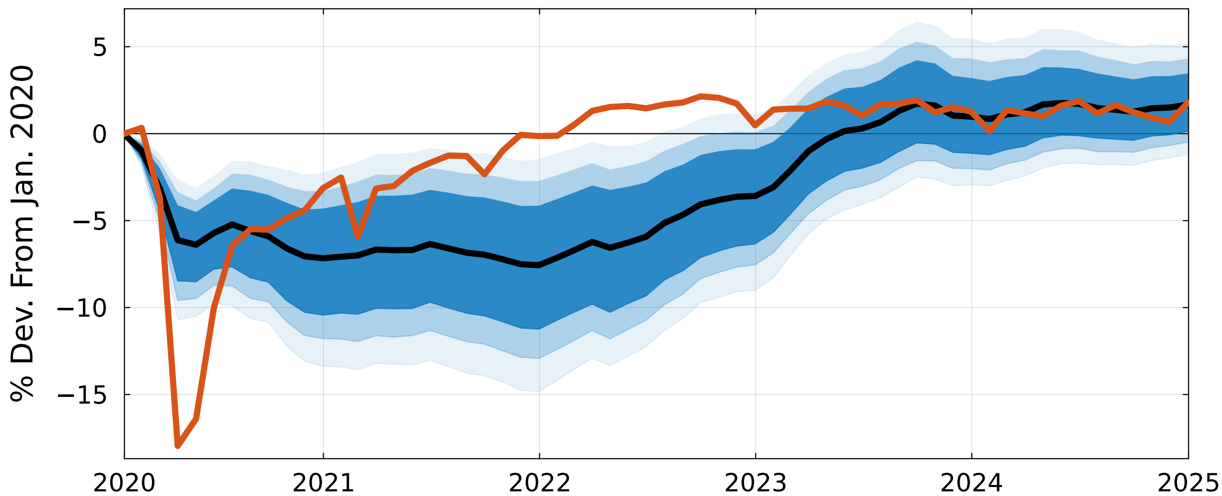

Figure 9: Historical Decomposition of Industrial Production

Notes: The figures show the historical contribution of global supply chain shocks to the US Industrial Production in percentage deviation from the pre-pandemic level (January 2020). The solid orange line is the actual series, the solid black line is the point estimates, and the shaded areas are 68, 80 and 90 percent confidence bands, respectively.

compounded by strict COVID-19 containment measures, such as port controls, labor restrictions, and travel bans, which led to significant delays in the shipment of intermediate goods and sharply increased production costs.

In April 2020, global supply chain shocks accounted for nearly 34 percent of the total decline of industrial production, equivalent to a contraction of about 6 percent. This estimate is in line with the quantitative exercises of Brinca, Duarte and Faria-e Castro (2021) and Baqaee and Farhi (2022), who emphasize the substantial drag exerted by supply-side forces on economic activity during the early phase of COVID-19. While industrial production began to recover in the second half of 2020, the downward pressures from supply chain shocks intensified. Their contribution to the production shortfall peaked at -7.5 % in November 2021, in line with the findings of Alessandria et al. (2023). Their effect gradually declined thereafter, with the negative contribution dissipating by May 2023.

4.4 Summary

The historical decomposition analysis reveals that global supply chain shocks played a more prominent role in the early phase of post-pandemic inflation than previously recognized. My findings confirm the central importance of these shocks in shaping inflation dynamics in 2021. However, I do not dismiss the role of demand-side forces: large-scale fiscal stimulus and pent-up demand also contributed meaningfully to the inflationary surge. In particular, beginning in the second half of 2021, my results suggest that other shocks increasingly became the dominant drivers of the price level, consistent with the timing of the massive fiscal recovery plan.

When viewed alongside the dynamics of industrial production, these results suggest that the fiscal response to the pandemic supported a faster recovery of real activity, advancing the timeline of production returning to pre-pandemic levels by roughly 18 months relative to a scenario with only global supply chain shocks. However, this recovery came at the cost of higher inflation, underscoring the trade-off between supporting output and anchoring prices during supply-side disturbances.

Finally, this analysis contributes a novel insight to the ongoing policy debate: while much of the discussion on global supply chain shocks has centered on their inflationary consequences (Tenreyro, 2021; Lane, 2022; Guerrieri et al., 2023), my findings show that these shocks also have long-lasting contractionary effects on real activity. This persistence highlights the importance of recognizing these shocks not only as a source of persistent inflation but also as a meaningful driver of output fluctuations over the business cycle.

5 Quantitative Importance

Forecast Error Variance Decomposition.— The preceding analysis has shown that global supply chain shocks are not only a source of persistent inflation but also a meaningful driver of output fluctuations over the business cycle. Building on this insight, I now turn to a formal quantification of their contribution to macroeconomic volatility. Specifically, I assess the average importance of global supply chain shocks in explaining forecast error variance across the aggregate variables in the baseline model. This allows me to evaluate how much of the business cycle is systematically accounted for by these shocks over different time horizons.

Under the identification assumptions of Section 3, if the structural impact vector $\widetilde{\boldsymbol{h}}_1$ is identified, the variance of the shock is also identified as

$$d_{11} = \widetilde{\boldsymbol{h}}_1' \boldsymbol{\Omega}^{-1} \widetilde{\boldsymbol{h}}_1 \tag{13}$$

where $\boldsymbol{\Omega}$ is the reduced-form variance-covariance matrix. Consequently, I compute the contribution of the global supply chain shock to the h-step-ahead forecast error variance-covariance matrix of $\boldsymbol{y}_t$ as

$$\sum_{s=0}^{h-1} \boldsymbol{\Psi}_h \widetilde{\boldsymbol{h}}_1 d_{11} \widetilde{\boldsymbol{h}}_1' \boldsymbol{\Psi}_h'. \tag{14}$$

The ratio of the diagonal elements of (14) to those of the diagonal elements of the overall h-step-ahead forecast error variance-covariance matrix, $\sum_{s=0}^{h-1} \boldsymbol{\Psi}_h \boldsymbol{\Omega} \boldsymbol{\Psi}_h'$, provides the percentage of the h-step-ahead variances of $\boldsymbol{y}_t$ accounted by the first structural shock.

Discussion.— Table 1 presents the results. The global supply chain shock accounts for the vast majority of fluctuations in the global supply chain pressure index, explaining almost 80% of its variance on impact and nearly 60% in the long run. In contrast, the shock contributes minimally to oil price variability, with almost none of the short-term variation attributed to global supply chain disruptions, confirming that oil prices are largely disconnected from such shocks. The shock's contribution to consumer price fluctuations is small in the first year but grows over the long term, accounting for 35% of CPI variability in the long run. Turning to real variables, the global supply chain shock plays a significant role in driving real business cycle fluctuations. It explains a substantial portion of industrial production variability, increasing from 16% on impact to almost 25% in the long run. The shock's contribution is modest for unemployment on impact, but becomes relevant after one year.

Table 1: Forecast Error Variance Decomposition

	US CPI	WTI Oil Price	US Ind. Prod.	US Unemp.	GSCPI
Horizon					
0	0.00	0.04	0.16	0.01	0.79
	[0.00, 0.10]	[0.02, 0.19]	[0.01, 0.40]	[0.00, 0.11]	[0.53, 0.97]
12	0.02	0.03	0.25	0.12	0.74
	[0.00, 0.19]	[0.00, 0.17]	[0.05, 0.54]	[0.01, 0.35]	[0.48, 0.93]
24	0.12	0.03	0.24	0.10	0.66
	[0.01, 0.39]	[0.00, 0.18]	[0.06, 0.53]	[0.00, 0.36]	[0.46, 0.84]
36	0.23	0.05	0.24	0.10	0.60
	[0.07, 0.53]	[0.00, 0.20]	[0.06, 0.53]	[0.00, 0.37]	[0.41, 0.78]
48	0.29	0.06	0.24	0.10	0.59
	[0.10, 0.60]	[0.00, 0.22]	[0.06, 0.52]	[0.00, 0.38]	[0.41, 0.77]
∞	0.35	0.07	0.24	0.09	0.58
	[0.12, 0.74]	[0.00, 0.25]	[0.08, 0.50]	[0.00, 0.35]	[0.40, 0.77]

Notes: The table shows the proportion of the forecast error variance of the variables in the baseline model explained by global supply chain shocks at horizons 0, 12, 24, 36, 48 months and in the long-run. The 90 percent confidence intervals are displayed in brackets.

Compared to the estimates of Bai et al. (2024), my findings attribute a larger share of long-run consumer price variability to global supply chain shocks, 35% versus their approximately 25% for personal consumption expenditure prices, while indicating a more gradual transmission on impact. More notably, my estimates imply a large role for global supply chain shocks in driving real activity. Bai et al. (2024) find a limited contribution to real GDP variance, while my results for industrial production suggest nearly double the explanatory power. Taken together with the impulse response and historical decomposition analysis, these results confirm that global supply chain shocks are not only a source of persistent inflationary pressures but also key contributors to business cycle fluctuations.

6 Sensitivity Analysis

In this section, I present a series of robustness checks to assess the stability of the main results. Specifically, I examine the sensitivity of the estimates to alternative specifications of the instrument by sequentially excluding individual categories of disruptions. I also revisit the invertibility assumption and explore alternative empirical strategies for identifying global supply chain shocks. Additional robustness checks related to control variables and lag length are provided in the online Appendix A.

6.1 Testing the Role of Individual Disruption Categories

The instrument is constructed from price surcharges associated with distinct types of exogenous supply-side disruptions: operational issues, armed conflict, labor strikes, and extreme weather or natural disasters. A key robustness check involves assessing whether the results are disproportionately driven by specific episodes or by particular types of disruptions.

Figure 10 displays the aggregate-level results obtained by sequentially excluding one category of disruptions at a time (column by column) from the instrument. The findings remain remarkably consistent with the baseline specification presented in Section 3, effectively ruling out the possibility that the results are driven by any single category of disruptions. Excluding the operational disruptions serves as the most stringent robustness check for two reasons. First, events classified under this category are more prone to be contaminated by other contemporaneous shocks compared to strikes, natural disasters, or conflict-related disruptions. Second, operational disruptions account for nearly 53% of all individual disruptions in the sample, making them quantitatively dominant. The stability of results even after their exclusion provides strong support for the robustness of the identification strategy.

Another key robustness check involves excluding all disruptions directly or indirectly related to the COVID-19 pandemic, given the exceptional nature of the COVID shock relative to standard macroeconomic shocks. Of the 62 identified exogenous supply chain disruptions,

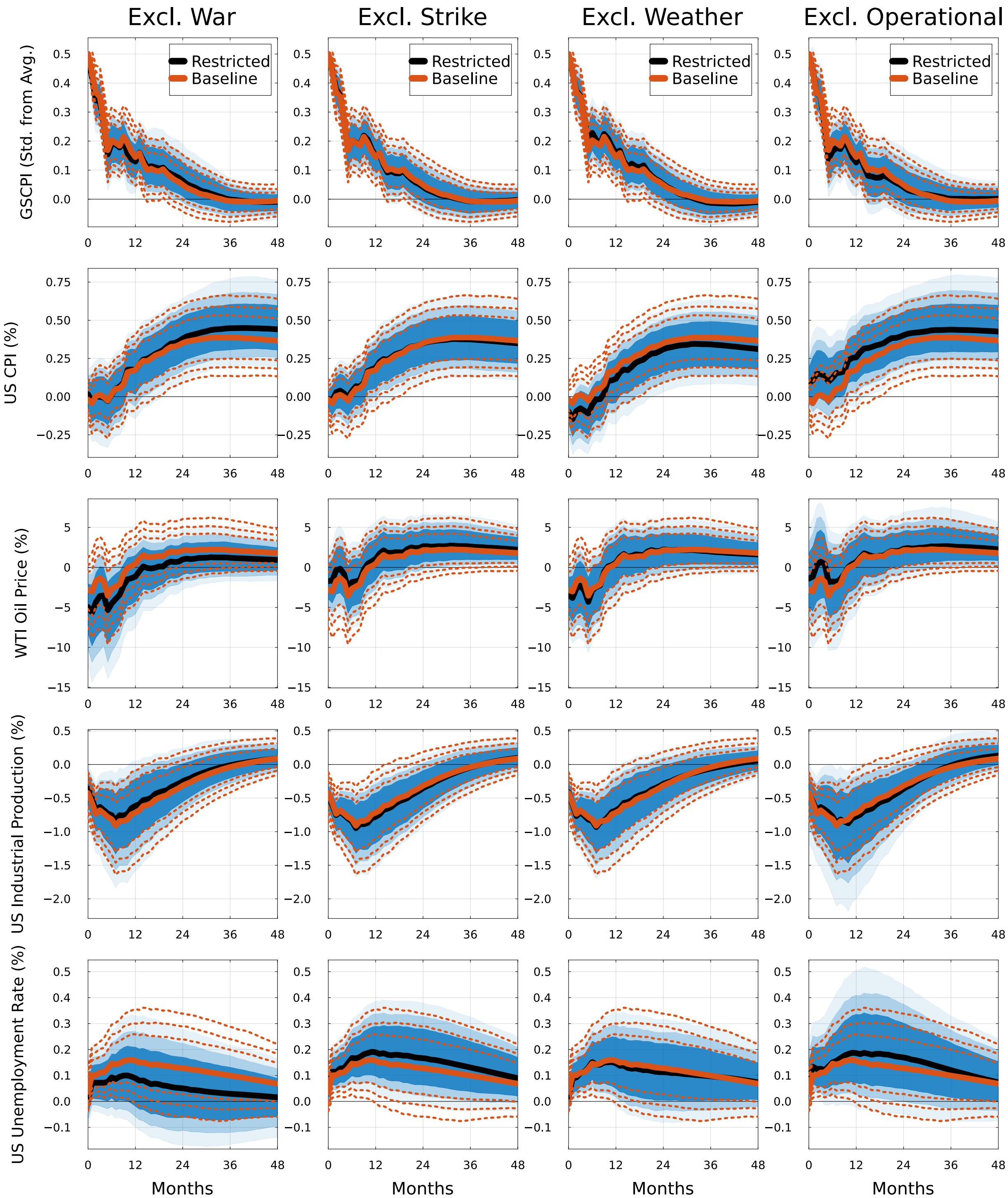

Figure 10: Robustness to Excluding Categories of Supply Chain Disruptions

Notes: Impulse responses to a global supply chain shock corresponding to a $1,340 price surcharge. Each column shows estimates excluding one category of surcharges (war, strike, climate, or operational) from the instrument. The orange lines represent the baseline specification, while the black lines represent the restricted estimates excluding the specified category. The solid lines represent the point estimates, and the shaded areas (and dotted lines) denote 68, 80, and 90 percent confidence bands, respectively.

14 are congestion events driven by pandemic-induced labor shortages, logistics and operational difficulties, or the implementation of additional sanitary protocols; one corresponds to a COVID-19 outbreak that led to the partial shutdown of the Ningbo port in China; and one reflects a strike in Northern Europe stemming from deteriorated labor conditions due to the pandemic. These 16 disruptions are excluded from the instrument to test whether pandemic-specific events disproportionately influence the baseline results.

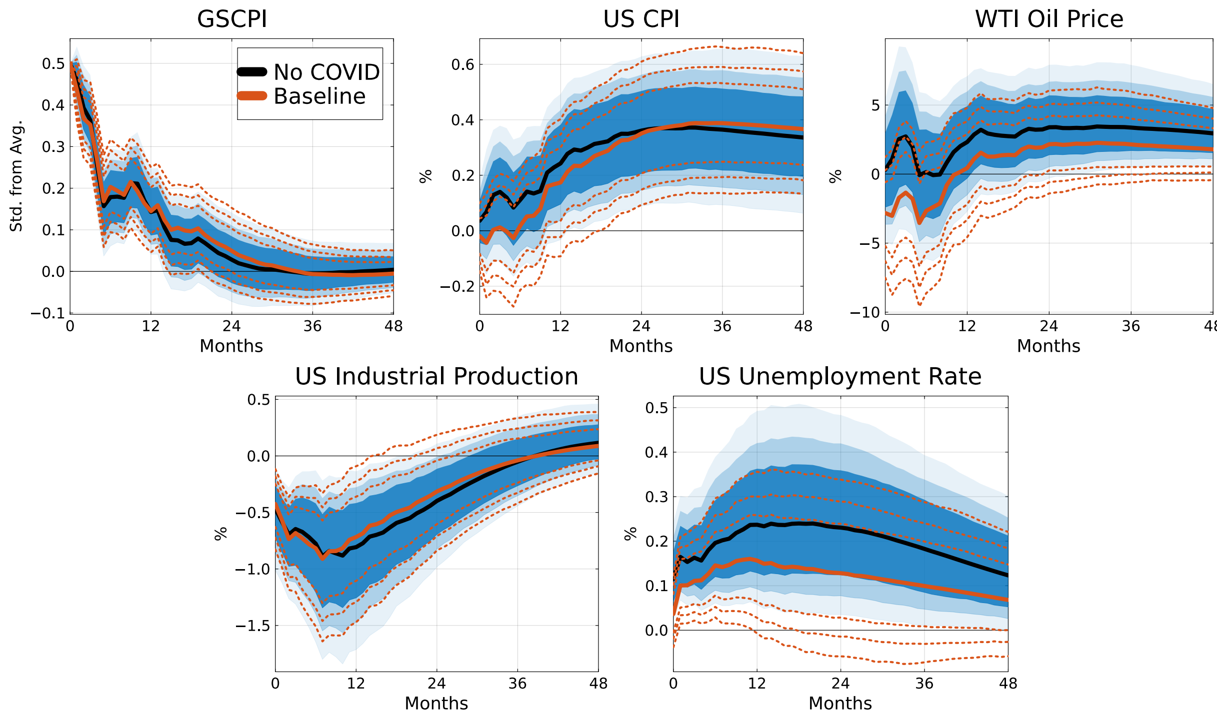

Figure 11: Robustness to Excluding COVID-Related Disruptions

Notes: Impulse responses to a global supply chain shock corresponding to a \$1,340 price surcharge. The orange lines represent the baseline specification, while the black lines represent the restricted estimates excluding the COVID-related disruptions. The solid lines represent the point estimates, and the shaded areas (and dotted lines) denote 68, 80, and 90 percent confidence bands, respectively.

As shown in Figure 11, the baseline results remain robust to the exclusion of COVID-related disruptions. The pass-through to consumer prices appears somewhat faster, while the effects on unemployment are stronger and more persistent. The responses of industrial production and the GSCPI remain virtually unchanged, and WTI oil price continues to exhibit no statistically significant response.

6.2 Invertibility Assumption

The identification strategy relies on the highly restrictive assumption of invertibility, meaning that the structural shocks at each time horizon lie within the linear span of current and lagged values of the endogenous variables. Fortunately, Plagborg-Møller and Wolf (2022) note that the invertibility assumption can be tested by assessing whether lagged values of the instrument contain predictive information for the current value of the endogenous variables beyond that provided by their own lags. I conduct a series of F-tests and find that the coefficients of the lagged instruments are statistically indistinguishable from zero across all endogenous variables in the baseline VAR model and for various lag lengths of the instrument, thereby failing to reject the null hypothesis of invertibility. In addition, I perform a joint test of the null hypothesis that all coefficients on past realizations of the instrument are jointly zero, following the procedure in Hamilton (Forthcoming), and again fail to reject the invertibility assumption (see online Appendix A). This finding is consistent with the nature of the identified shock. Unlike news shocks, which Ramey (2016) and Nakamura and Steinsson (2018) argue are a common source of invertibility violations, the global supply chain shock does not present the foresight problem. Furthermore, by construction, the GSCPI captures comprehensive information on global disruptions, reducing the likelihood of omitted information that might otherwise compromise invertibility.

Given that the data do not reject invertibility, there is no need to rely on the internal instrument approach proposed by Plagborg-Møller and Wolf (2022), which relaxes this assumption by requiring the instrument to be orthogonal to structural shocks at all leads and lags. Moreover, the internal instrument approach is infeasible in my context because it requires the instrument to be observed over the full sample period in order to be ordered first in the VAR. Since the FEU price surcharge series has a shorter time span than the other VAR variables, I instead adopt the Proxy-SVAR framework, which flexibly accommodates instruments with limited history by separating the identification and estimation samples.

6.3 Local Projection - Instrumental Variable

Beyond the standard relevance and exogeneity conditions and the invertibility assumption, the consistency of structural impulse response functions also relies on the VAR model adequately capturing the covariance structure of the data. In a VAR(p) model, long-run responses are extrapolated from the first p sample autocovariances, which may lead to biased estimates if the lag length is misspecified (Montiel Olea et al., 2025). An alternative approach is to estimate dynamic causal effects using local projections, which are less sensitive to model misspecification and do not impose a specific dynamic structure. However, the local projection–instrumental variable (LP-IV) approach poses challenges in this setting due to the short sample of the external instrument. Estimating a separate IV regression at each horizon reduces the effective sample size, particularly at longer horizons, resulting in a substantial loss of statistical power.

To address this, I implement a battery of LP-IV regressions à la Jordà (2005) using the global supply chain shock identified from the Proxy-SVAR as the regressor of interest:

$$\boldsymbol{y}_{t+h} = \boldsymbol{\Theta}_{h,1}\hat{u}_{1t} + \boldsymbol{\Pi}\boldsymbol{x}_{t-1} + \boldsymbol{\eta}_{t+h} \; . \tag{15}$$

Here, $\boldsymbol{y}_{t+h}$ denotes the vector of outcome variables at horizon h, $\hat{u}_{1t}$ is the identified global supply chain shock, and $\boldsymbol{x}_{t-1}$ is a vector of controls, including twelve lags of the outcome variables. Using $\hat{u}_{1t}$ instead of the FEU price surcharge series overcomes the power limitations of the LP-IV framework, as it is available over the full sample starting in 1998.

Figure 12 compares the IRFs obtained from the Proxy-SVAR and LP-IV approaches. The responses are remarkably similar across both short and long horizons, providing evidence that the baseline VAR captures the underlying covariance structure of the data. As expected, the local projections are more erratic, as no dynamic restrictions are imposed across impulse horizons.

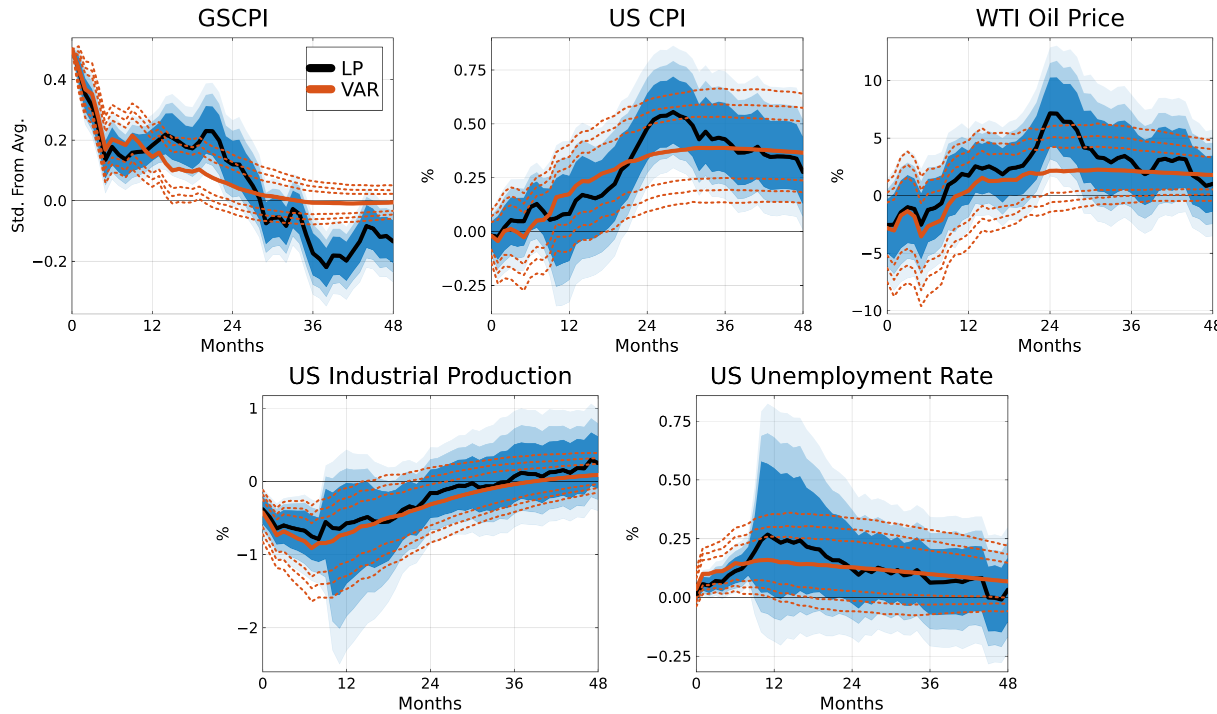

Figure 12: Proxy-SVAR vs. Local Projection Responses

Notes: Impulse responses to a global supply chain shock corresponding to a $1,340 price surcharge. The orange lines represent the baseline Proxy-SVAR results, while the black lines represent the LP-IV results. The solid lines represent the point estimates, and the shaded areas (and dotted lines) denote 68, 80, and 90 percent confidence bands, respectively.

7 Conclusion

This paper presents a novel identification strategy to assess the impact of shocks to the global supply chain on the macroeconomy. I identify 62 exogenous disruptions worldwide, derived from a narrative analysis of almost 7,000 price and surcharge updates from the three largest container shipping companies. These shocks have significant aggregate effects on the macroeconomy and act as cost-push factors, raising prices persistently and exerting long-lasting downward pressure on economic activity.

I show that these shocks produce a broad-based contraction across all major production sectors and trigger persistent increases in consumer prices across nearly all major CPI subcategories. The magnitude of these effects varies systematically with each sector's exposure to the global supply chain, measured by the percentage of production inputs outsourced abroad.

I demonstrate that sectors with higher exposure experience sharper output contractions and stronger price pass-through. Beyond the tradable goods sector, I find that global supply chain shocks spill over into non-tradable services. Although the response of service activity and employment is more modest and transitory, it highlights the wider macroeconomic reach of the global supply chain shocks.

I show that negative shocks to the global supply chain were the dominant drivers of inflation in the early stages of the post-pandemic period, accounting for an average of 51% of the increase in consumer prices in 2021. This contribution diminished over time but remained significant in 2022 (32%), 2023 (30%), and 2024 (22%). I also find that these shocks imposed a substantial drag on economic recovery. In a counterfactual scenario with only global supply chain shocks, industrial production would have returned to pre-pandemic levels 18 months later than it did. This highlights a trade-off: the fiscal stimulus of late 2021 accelerated the recovery but at the cost of higher inflation.

I further demonstrate that global supply chain shocks are significant drivers of business cycle fluctuations, accounting for approximately 25% of the long-run variance in industrial production and 35% of the variance in consumer prices, thereby positioning them as key contributors to business cycle fluctuations.

I found that these results are robust across a wide range of empirical specifications, including alternative identification schemes, identification assumptions, and different specifications of the instrument. My identification strategy, centered on shipping company surcharges, offers a credible way to isolate exogenous supply-side disruptions.

References

Acemoglu, Daron, and Alireza Tahbaz-Salehi. 2020. “Firms, failures, and fluctuations: the macroeconomics of supply chain disruptions.” National Bureau of Economic Research.

Acemoglu, Daron, and Alireza Tahbaz-Salehi. 2025. "The Macroeconomics of Supply Chain Disruptions." *Review of Economic Studies*, 92(2): 656–695.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The network origins of aggregate fluctuations." *Econometrica*, 80(5): 1977–2016.

Alessandria, George, Shafaat Yar Khan, Armen Khederlarian, Carter Mix, and Kim J Ruhl. 2023. "The aggregate effects of global and local supply chain disruptions: 2020–2022." *Journal of international Economics*, 146: 103788.

Alquist, Ron, Saroj Bhattarai, and Olivier Coibion. 2020. "Commodity-price comovement and global economic activity." *Journal of Monetary Economics*, 112: 41–56.

Aruoba, S Boragan, and Thomas Drechsel. 2024. "Identifying monetary policy shocks: A natural language approach." National Bureau of Economic Research.

Ascari, Guido, Dennis Bonam, and Andra Smadu. 2024. "Global supply chain pressures, inflation, and implications for monetary policy." *Journal of International Money and Finance*, 142: 103029.

Bai, Xiwen, Jesús Fernández-Villaverde, Yiliang Li, and Francesco Zanetti. 2024. "The causal effects of global supply chain disruptions on macroeconomic outcomes: evidence and theory." National Bureau of Economic Research.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. "Measuring economic policy uncertainty." *The Quarterly Journal of Economics*, 131(4): 1593–1636.

Baldwin, Richard, Rebecca Freeman, and Angelos Theodorakopoulos. 2023. "Hidden exposure: Measuring US supply chain reliance." *Brookings Papers on Economic Activity*, 2023(2): 79–167.

Baqaee, David, and Emmanuel Farhi. 2022. "Supply and demand in disaggregated Keynesian economies with an application to the Covid-19 crisis." *American Economic Review*, 112(5): 1397–1436.

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

Baumeister, Christiane, and James D Hamilton. 2019. "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks." *American Economic Review*, 109(5): 1873–1910.

Baumeister, Christiane, and James D Hamilton. 2024. "Advances in using vector autoregressions to estimate structural magnitudes." *Econometric Theory*, 40(3): 472–510.

Baumeister, Christiane, Dimitris Korobilis, and Thomas K Lee. 2022. "Energy markets and global economic conditions." *Review of Economics and Statistics*, 104(4): 828–844.

Benigno, Gianluca, Julian Di Giovanni, Jan J Groen, and Adam I Noble. 2022. "The GSCPI: A new barometer of global supply chain pressures." FRB of New York Staff Report 1017.

Bergholt, Drago, Fabio Canova, Francesco Furlanetto, Nicolò Maffei-Faccioli, and Pål Ulvedal. Forthcoming. "What drives the recent surge in inflation? The historical decomposition roller coaster." *American Economic Journal: Macroeconomics.*

Bernanke, Ben, and Olivier Blanchard. 2023. "What caused the US pandemic-era inflation?" *PIIE, Peterson Institute for International Economics*, 86.

Bernanke, Ben, and Olivier Blanchard. 2024. "An Analysis of Pandemic-Era Inflation in 11 Economies." National Bureau of Economic Research.

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar. 2019. "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake." *Review of Economics and Statistics*, 101(1): 60–75.

Brinca, Pedro, Joao B Duarte, and Miguel Faria-e Castro. 2021. "Measuring labor supply and demand shocks during COVID-19." *European Economic Review*, 139: 103901.

Caldara, Dario, Matteo Iacoviello, and David Yu. 2025. "Measuring shortages since 1900." International Finance Discussion Paper 1407.

Caldara, Dario, Michele Cavallo, and Matteo Iacoviello. 2019. "Oil price elasticities and oil price fluctuations." *Journal of Monetary Economics*, 103: 1–20.

Carrière-Swallow, Yan, Pragyan Deb, Davide Furceri, Daniel Jiménez, and Jonathan D Ostry. 2023. "Shipping costs and inflation." *Journal of International Money and Finance*, 130: 102771.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. 2021. "Supply chain disruptions: Evidence from the great east japan earthquake." *The Quarterly Journal of Economics*, 136(2): 1255–1321.

Cochrane, John H. 2022. "Inflation past, present and future: Fiscal shocks, Fed response, and fiscal limits." National Bureau of Economic Research.

Comin, Diego A, Robert C Johnson, and Callum J Jones. 2023. "Supply chain constraints and inflation." National Bureau of Economic Research.

Davis, Steven J, and John Haltiwanger. 2001. "Sectoral job creation and destruction responses to oil price changes." *Journal of monetary economics*, 48(3): 465–512.

Delle Chiaie, Simona, Laurent Ferrara, and Domenico Giannone. 2022. "Common factors of commodity prices." *Journal of Applied Econometrics*, 37(3): 461–476.

De Santis, Roberto A. 2024. "Supply chain disruption and energy supply shocks: impact on euro area output and prices."

Di Giovanni, Julian, Şebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A Yıldırım. 2023*a*. "Quantifying the inflationary impact of fiscal stimulus under supply constraints." Vol. 113, 76–80, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Di Giovanni, Julian, Ṣebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A Yildirim. 2022. "Global supply chain pressures, international trade, and inflation." National Bureau of Economic Research.

Di Giovanni, Julian, Ṣebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A Yildirim. 2023*b*. "Pandemic-era inflation drivers and global spillovers." National Bureau of Economic Research.

Elliott, Matthew, and Benjamin Golub. 2022. "Networks and economic fragility." *Annual Review of Economics*, 14(1): 665–696.

Elliott, Matthew, Benjamin Golub, and Matthew V Leduc. 2022. "Supply network formation and fragility." *American Economic Review*, 112(8): 2701–2747.

Fan, Lei, William W Wilson, and Bruce Dahl. 2012. "Congestion, port expansion and spatial competition for US container imports." *Transportation Research Part E: Logistics and Transportation Review*, 48(6): 1121–1136.

Faria-e Castro, Miguel. 2024. "The St. Louis Fed DSGE Model." FRB of St. Louis Working Paper.

Finck, David, and Peter Tillmann. 2022. "The macroeconomic effects of global supply chain disruptions." *BOFIT Discussion Paper*.

Gabaix, Xavier. 2011. "The granular origins of aggregate fluctuations." *Econometrica*, 79(3): 733–772.

Garcia Revelo, Jose David, Gregory Levieuge, and Jean-Guillaume Sahuc. Forthcoming. "Revisiting 15 Years of Unusual Transatlantic Monetary Policies." *Journal of International Money and Finance*.

Giannone, Domenico, and Giorgio Primiceri. 2024. "The drivers of post-pandemic inflation." National Bureau of Economic Research.

Goda, Gopi Shah, and Evan J Soltas. 2022. "The impacts of Covid-19 illnesses on workers." *Journal of Public Economics*, 222.

Gordon, Matthew V, and Todd E Clark. 2023. "The impacts of supply chain disruptions on inflation." Economic Commentary, Federal Reserve Bank of Cleveland 2023-08.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning. 2022. "Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?" *American Economic Review*, 112(5): 1437–1474.

Guerrieri, Veronica, Michala Marcussen, Silvana Tenreyro, and Lucrezia Reichlin. 2023. *The art and science of patience: relative prices and inflation.* Centre for Economic Policy Research (CEPR).

Hamilton, James D. 1985. "Historical causes of postwar oil shocks and recessions." *The Energy Journal*, 6(1): 97–116.

Hamilton, James D. 2003. "What is an oil shock?" *Journal of econometrics*, 113(2): 363–398.

Hamilton, James D. 2009. "Causes and Consequences of the Oil Shock of 2007-08." National Bureau of Economic Research.

Hamilton, James D. Forthcoming. *Vector Autoregressions.* Cambridge University Press.

Hazell, Jonathon, and Stephan Hobler. 2024. *Do Deficits Cause Inflation?: A High Frequency Narrative Approach.* London School of Economics and Political Science.

Herrera, Ana María, Latika Gupta Lagalo, and Tatsuma Wada. 2011. "Oil price shocks and industrial production: Is the relationship linear?" *Macroeconomic dynamics*, 15(S3): 472–497.

Hobijn, Bart, and Aysegul Sahin. 2022. ""Missing" Workers and "Missing" Jobs Since the Pandemic." FRB of Chicago Working Paper 2022-54.

Jordà, Òscar. 2005. "Estimation and inference of impulse responses by local projections." *American economic review*, 95(1): 161–182.

Jordà, Òscar, and Fernanda Nechio. 2023. "Inflation and wage growth since the pandemic." *European Economic Review*, 156: 104474.

Känzig, Diego R, and Ramya Raghavan. 2025. "The Macroeconomic Effects of Supply Chain Shocks: Evidence from Global Shipping Disruptions." *Presentation Slides, NBER Summer Institute 2025.*

Lane, Philip. 2022. "Bottlenecks and monetary policy." *ECB blog.*

Lee, Dain, Jinhyeok Park, and Yongseok Shin. 2023. "Where are the workers? From great resignation to quiet quitting." National Bureau of Economic Research.

Lenza, Michele, and Giorgio E Primiceri. 2022. "How to estimate a vector autoregression after March 2020." *Journal of Applied Econometrics*, 37(4): 688–699.

Mertens, Karel, and Morten O Ravn. 2013. "The dynamic effects of personal and corporate income tax changes in the United States." *American economic review*, 103(4): 1212–1247.

Montiel Olea, José L, James H Stock, and Mark W Watson. 2021. "Inference in structural vector autoregressions identified with an external instrument." *Journal of Econometrics*, 225(1): 74–87.

Montiel Olea, José Luis, Mikkel Plagborg-Moller, Eric Qian, and Christian Wolf. 2025. "Local Projections or VARs? A Primer for Macroeconomists." NBER Working Paper w33871.

Nakamura, Emi, and Jón Steinsson. 2018. "Identification in macroeconomics." *Journal of Economic Perspectives*, 32(3): 59–86.

Notteboom, Theo, Athanasios Pallis, and Jean-Paul Rodrigue. 2022. *Port economics, management and policy.* Routledge.

Plagborg-Møller, Mikkel, and Christian K Wolf. 2022. "Instrumental variable identification of dynamic variance decompositions." *Journal of Political Economy*, 130(8): 2164–2202.

Qureshi, Irfan A, and Ghufran Ahmad. 2025. "Oil price shocks and US business cycles." *Journal of Economic Dynamics and Control*, 105132.

Ramey, Valerie A. 2011. "Identifying government spending shocks: It's all in the timing." *The Quarterly Journal of Economics*, 126(1): 1–50.

Ramey, Valerie A. 2016. "Macroeconomic shocks and their propagation." *Handbook of macroeconomics*, 2: 71–162.

Ramey, Valerie A, and Matthew D Shapiro. 1998. "Costly capital reallocation and the effects of government spending." *Carnegie-Rochester conference series on public policy*, 48: 145–194.

Romer, Christina D, and David H Romer. 2004. "A new measure of monetary shocks: Derivation and implications." *American economic review*, 94(4): 1055–1084.

Romer, Christina D, and David H Romer. 2010. "The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks." *American economic review*, 100(3): 763–801.

Rubbo, Elisa. 2024. "What drives inflation? Lessons from disaggregated price data." National Bureau of Economic Research.

Shapiro, Adam Hale. 2024. "Decomposing Supply-and Demand-Driven Inflation." *Journal of Money, Credit and Banking.*

Stock, James H. 2008. "What's new in Econometrics: Time Series, lecture 7." *Short course lectures, NBER Summer Institute.*

Stock, James H, and Mark W Watson. 2016. "Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics." In *Handbook of macroeconomics.* Vol. 2, 415–525. Elsevier.

Stock, James H, and Mark W Watson. 2018. "Identification and estimation of dynamic causal effects in macroeconomics using external instruments." *The Economic Journal*, 128(610): 917–948.

Tenreyro, Silvana. 2021. "International trade, global supply chains and monetary policy." *Speech given at the Centre for Economic Policy Research webinar.*

Tenreyro, Silvana. 2022. "The path to 2 percent." *Speech at the Society of Professional Economists Annual Conference, London.*